Working Remotely and the Supply-side Impact of Covid-19*

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Abstract

We analyze the supply-side disruptions associated with Covid-19 using differences in the ability of workers to work remotely. Sectors in which a higher fraction of the workforce is not able to work remotely experienced greater declines in employment and expected revenue growth, worse stock market performance, and higher likelihood of default. Lower-paid workers, especially female workers with young children, were significantly more affected by these disruptions. The stock market overweighs low-exposure industries, helping explain the disconnect between stock market indices and aggregate outcomes. Further, we find evidence that the Paycheck Protection Program provided less relief per-employee to the most exposed sectors. Finally, we combine these ex-ante heterogeneous industry exposures with daily financial market data to create a stock return portfolio that most closely replicates the supply-side disruptions resulting from the pandemic.

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The Covid-19 pandemic of 2020 has led to severe disruptions to the supply side of the world economy as entire sectors shut down. In the first quarter of 2020, US gross domestic output fell by 4.8 percent in annualized terms, a decline not seen since the Great Recession. This drop underestimates the full economic impact of the pandemic, as the severity of the crisis became fully apparent to the public and private sector only in the last few weeks of March. Moreover, the effect has been highly asymmetric: restaurants, entertainment, and travel services suffered significantly more than food or technology services. Naturally, these declines reflect not only the supply-side disruptions due to the effect of the lockdown but also demand-side factors, including the collapse of global consumer demand and expectations of future government policy. This confluence of adverse forces obscures the direct effects of the supply-side disruptions of the pandemic.

Our goal is to isolate the supply side effects from other forces. Here, by supply side disruptions, we are referring to all the disruptions that prevented certain businesses from operating effectively in the middle of the pandemic; these include disruptions in both the production process but also difficulties in delivering their product or service to the final customer. Our starting point is that industries in which a higher fraction of the labor force can work remotely are likely to experience less severe disruptions in their business operations. We build on existing work and construct a metric of industry exposure to the lockdowns using information on the share of the workforce that can work from home (Dingel and Neiman, 2020; Alon, Doepke, Olmstead-Rumsey, and Tertilt, 2020). Specifically, we follow Alon et al. (2020) and exploit data from the American Time Use Survey (ATUS) in 2017 and 2018, in which workers disclose the extent to which they are able to and have historically had experience working remotely. As noted by Alon et al. (2020), occupations vary immensely by whether people report they are able to telecommute—ranging from 3% for transportation and material moving to 78% for computer programmers. We aggregate these survey responses to build measures of exposure across industries and groups of workers.

In brief, our measure of supply side disruption for a given industry, termed "Covid-19 work exposure," is equal to one minus the fraction of workers that have telecommuted – more specifically, the fraction that have ever worked full days from home – in each industry. Importantly, there is considerable dispersion in our exposure measure across industries. For example, software publishers (NAICS 5112) have an exposure of just 0.38, since much of the production work can be done remotely; by contrast, meat production (NAICS 3116) or general merchandise store (NAICS 4523) workers have an exposure close to one, since most of the employees cannot perform their work remotely.

In addition, government restrictions also play a role in firms' ability to continue operations. Specifically, local governments typically deem certain industries as critical, namely those that provide 'essential infrastructure'. Thus, we also manually classify some industries as 'essential'. Since the definition of essential industries varies greatly across states, we aim to be conservative, classifying as essential industries related to the production and sale of food and beverages; utilities; pharmacies;

transportation; waste collection and disposal; and some healthcare and financial services. Data on foot-traffic from *SafeGraph* validate our construction: establishments in industries deemed critical experience significantly smaller declines in traffic than establishments in non-critical industries, which stands in stark contrast to nearly identical trends in foot traffic from January to February 2020.

Armed with a measure of industry exposure to these supply-side disruptions, we can answer several important questions regarding the economic impact of the pandemic. Focusing on cross-sectional differences in the feasibility of remote work (Covid-19 work exposure) allows us to isolate the direct impact of the shutdown from other economic forces that would otherwise affect the economy symmetrically.

First, we examine the degree to which differences in Covid-19 work exposure are related to heterogeneity in economic outcomes during the pandemic. In terms of employment, we find that sectors with a larger fraction of workers who cannot work remotely—higher Covid-19 work exposure—experienced significantly larger declines in employment than sectors where more of the workforce can perform tasks remotely. The differences are economically sizable: a one-standard deviation increase in our Covid-19 work exposure measure is associated with an approximately 7 percent larger decline in employment since April of 2019; the differences among sectors is starker when we restrict the sample to non-critical industries (10 percent).

We next focus on firm outcomes. Given the delays in the availability of data on firms' real activity, we focus on a set of forward-looking variables that capture future expectations about fundamentals. That is, we focus on the revisions in analyst forecasts of expected revenue growth, the expected probability of default, and firm survey responses. We find that firms in sectors that are more likely to experience work disruptions also fare significantly worse during the 2020 pandemic: a one-standard-deviation increase in our Covid-19 exposure metric is associated with a 8 percent decline in analysts' revenue forecasts for Q2 and a 0.22 percentage point increase in the probability of default over the next 6 months. These magnitudes account for a significant share of cross-industry differences in outcomes during this period. Importantly, while financial analysts expect the worst effects to be short-lived, our work exposure variable is still a significant predictor of differences in expected revenue growth over the next two years—though magnitudes are significantly muted. Similar patterns emerge in the differences in projected revenue for non-critical versus critical industries; while analysts project that the annual revenues of firms in non-critical industries will decline by 13, 10, and 8 percent for 2020, 2021, and 2022, respectively, these same projected declines are 3.2, 2.5, and 2.3 percent for firms in critical industries. Last, firm-level surveys confirm that our Covid-19 exposure measure is predictive of economic hardship during the pandemic: it is indicative of both employee layoffs and insufficient liquidity.

We next turn our attention to stock market valuations. We find that differences in our covid work exposure measure are significantly related to differences in stock returns during the early phase of the pandemic (February to May 2020). A one standard deviation increase in our exposure measure is associated with a 7 percent decline in stock market performance. Further, a key advantage of financial market variables is that they are available at high frequencies. To this end, we use financial market data to construct a real-time indicator of supply-side disruptions. In particular, we use daily data on stock returns to construct a portfolio that is maximally exposed to the Covid-19 work disruption using the methodology of Fama and MacBeth (1973). The resulting 'Covid-19' factor has a long-short portfolio interpretation. It overweighs industries whose workers cannot work remotely and underweighs industries whose workers can perform their tasks from home. As of May 15, 2020, this portfolio had lost roughly 50 percent of its value since the beginning of the year—compared to 10 percent for the broad market index. Naturally, reversing this investment strategy would deliver a portfolio that could significantly hedge future Covid-19 related uncertainty.

Comparing the performance of the stock market to the real economy in 2020 reveals an apparent disconnect. After falling sharply in late February and early March, the stock market had almost fully recovered its losses by the middle of the summer. By contrast, the economy is still in a severe recession, as evidenced by high unemployment rates. Our measure sheds some light on this pattern: the composition of listed firms in the stock market is heavily tilted towards *low work exposure* industries. As an illustration, we note that the average industry has an exposure of only 66% when weighting industries according to the market capitalization of listed firms, which is considerably lower than the 87% obtained by weighting the same set of industries according to a measure of employment of all firms (publicly and privately held) in the sector. Likewise, stock market indices which weigh industries according to the same measure of employment are almost 10 percentage points lower than a market capitalization-weighted index.

So far, our analysis indicates that the supply-side disruptions are economically large and are responsible for substantial heterogeneity in outcomes across sectors. Our results thus complement the work of Barrero, Bloom, and Davis (2020) who highlight that Covid-19 is also a reallocation shock. The relative differences that we uncover validate this view: the Covid-19 pandemic, in addition to its aggregate effects, led to a reallocation of resources away from sectors in which remote work is infeasible toward sectors where workers can continue to work remotely.

Most importantly, however, this cross-sectoral reallocation was not the only distributional effect of the Covid-19 pandemic. We also find that the pandemic affected workers differentially based on their demographic characteristics. Specifically, a given increase in our Covid-19 work exposure measure is associated with a greater increase in the probability of non-employment for women and lower-earning workers versus other groups. Among all affected groups, we find that the employment status of female workers with young children and without a college degree is most sensitive: in the cross-section of workers, a one-standard deviation increase in our Covid-19 work exposure measure is associated with a 15 percent probability of non-employment for these workers, which is more than three times the magnitude of the baseline coefficient. To the extent these effects are persistent, our findings would suggest that the pandemic will increase income inequality and magnify earnings differences between male and female workers.

In response to the pandemic, the government has authorized significant fiscal responses. A key component of the 2020 Coronavirus Aid, Relief, and Economic Security (CARES) Act was the Paycheck Protection Program (PPP)—a direct subsidy to firms that took the form of forgivable loans. Our exposure measure can also help judge the efficiency of this response: we would expect that a greater proportion of funds would be allocated to the most exposed industries. Perhaps surprisingly, we find the opposite.

In particular, almost all small firms applied for PPP financing. Importantly, however, funds were allocated in proportion to total payroll expenses. Since higher-paid employees are more likely to be able to work remotely, tying financing to payroll expenses had the (likely unintended) consequence of allocating more federal funds to the least affected sectors. For instance, firms in the "Professional and Technical Services," one of the least exposed sectors, received more than $12,400 per employee. By contrast, firms in "Accommodation and Food Services," one of the most affected sectors, received approximately $5,000 per worker. Using data at the individual loan level, we find that a one-standard deviation change in our measure of work exposure is associated with a 17% decline in the average loan size per employee, and a 19% decline in average loan size per employee when limiting the sample to non-critical industries. This negative correlation between the amount of federal aid and the degree workers were affected by the pandemic is likely at odds with an optimal policy prescription (see, e.g. Guerrieri, Lorenzoni, Straub, and Werning, 2020) but consistent with evidence from Granja, Makridis, Yannelis, and Zwick (2020) suggesting that PPP loans did not disproportionately flow to more adversely affected regions. A more targeted intervention likely would have been a more efficient use of federal funds in stimulating aggregate output—given the fact that lower-income workers have higher marginal propensities to consume (see, e.g. Kaplan and Violante, 2018, for a review of the literature).

Our work contributes to the voluminous economics literature that has emerged in response to the pandemic. The key differentiator of our work is its focus on isolating the supply side disruptions associated with Covid-19 by exploiting cross-sectional differences in the ability to work remotely. By contrast, existing work has focused on the overall response of the economy during this period.[1] How firms respond during the pandemic is a function of both the underlying supply-side disruptions (our focus) but also firms' exposures to a decline in consumer demand as a result of expected income losses and increase in uncertainty. Our goal is to isolate the former rather the latter channel. In this respect, our work is closer to Bonadio, Huo, Levchenko, and Pandalai-Nayar (2020) who focus on

[1] Recent work examines the response of employment (Coibion, Gorodnichenko, and Weber, 2020b; Cajner, Crane, Decker, Grigsby, Hamins-Puertolas, Hurst, Kurz, and Yildirmaz, 2020; Campello, Kankanhalli, and Muthukrishnan, 2020; Borjas and Cassidy, 2020; Fairlie, Couch, and Xu, 2020); firm revenue, earnings and dividends, (Barrero et al., 2020; Landier and Thesmar, 2020; Gormsen and Koijen, 2020); firm exit (Bartik, Bertrand, Cullen, Glaeser, Luca, and Stanton, 2020); stock market performance (Ding, Levine, Lin, and Xie, 2020; Giglio, Maggiori, Stroebel, and Utkus, 2020; Baker, Bloom, Davis, Kost, Sammon, and Viratyosin, 2020); or consumer spending Baker, Farrokhnia, Meyer, Pagel, and Yannelis (2020); Coibion, Gorodnichenko, and Weber (2020a) during this period.

the role of global supply chains; Davis, Hansen, and Seminario-Amez (2020) who estimate firm-level pandemic risk exposures using textual analysis of pre-pandemic 10-K filings; or Hassan, Hollander, van Lent, and Tahoun (2020) who identify differences in firms' exposure based on the transcript of analyst calls.

Last, our paper is related to recent work by Dingel and Neiman (2020), Alon et al. (2020), Mongey, Pilossoph, and Weinberg (2020) and Koren and Peto (2020). Dingel and Neiman (2020) and Koren and Peto (2020) construct measures of the feasibility of workers to work from home, but they do so using task descriptions in the ONET survey. Like us, Alon et al. (2020) construct a measure based on workers' answers to the American Time Use Survey (ATUS). Though the details of the construction differ, the main idea is similar. Dingel and Neiman (2020) and Alon et al. (2020) mainly focus on demographic differences among workers who can and cannot work remotely; by contrast, we are interested in how the ability to work from home is related to outcomes. In this respect, our work is closest to Mongey et al. (2020) and Koren and Peto (2020), who explore how the feasibility of remote work combined with measures of high physical proximity requirements relate to differential outcomes across workers. Though the first part of our analysis also explores worker-level outcomes, our primary focus is on firms. In contemporaneous work, Pagano, Wagner, and Zechner (2020) examine how the Koren and Peto (2020) measure is related to differences in stock market performance and argue that "pandemic risk" was priced in the 2014-19 period. Our focus instead is on understanding ex-post heterogeneity in economic outcomes. In this regard, we view our work as complementary.

1 Measuring Covid-19 Production Disruptions

We begin with a brief description of our construction of exposure measures from the data.

1.1 Workers' ability to work remotely

Following the rapid increase in cases throughout the US, many employers as well as state and local governments quickly imposed restrictions requiring that workers stay at home, leading to what is essentially the largest global experiment in telecommuting in human history. Our starting point is the simple premise that supply-side disruptions are likely to be more severe in occupations/industries for which workers have had little to no ability to or experience with telework in the past. Accordingly, our measure of industry exposure to work disruptions due to Covid-19 builds on Alon et al. (2020), who use data from the Leave and Job Flexibilities module of the American Time Use Survey (ATUS) in 2017 and 2018 (containing 10,040 observations in total), which asks several questions about workers' ability and past experiences with working from home. Our preferred measure utilizes responses to two different questions, though the module also includes several additional questions about reasons for and frequency of remote work. We obtain the ATUS microdata from IPUMS.[2]

Crucially, the survey draws a distinction between workers who are *able* or unable to telecommute, as opposed to actually regularly telecommuting, as the former is the relevant metric during a pandemic.[3] The output of this procedure is an occupation/industry-level metric of the fraction of workers in each occupation that should in principle be able to work from home. The first major question asks for a yes/no reply on whether "As part of your (main) job, can you work at home?" Using the survey's person weights, approximately 78% of households answer yes to this question. Alon et al. (2020) construct a measure of telework experience by identifying the share of workers in a given occupation that, according to their answers to this question, are able to telecommute, and provide several facts about the share of workers in various demographic groups which are employed in occupations which can be performed from home.

Our preferred measure also makes use of responses to one additional question, "Are there days when you work only at home?" which is only asked to those who say that they are able to work from home. Around 51% of households who are able to work from home also indicate that they have worked days entirely from home. In our view, answering this question in the affirmative provides a sharper classification of workers who will more likely be able to perform the majority of their job responsibilities from home, as opposed to only a subset of tasks (e.g., answering emails/phone calls) remotely. For example, 64% of computer and information systems managers (occupation 110) say that they can work from home, and 47% of them have worked days entirely from home. These same proportions are 59% and just 13%, respectively, for medical and health services managers (occupation 350), a group that, in our view, is a part of a population which is more likely to be unable to work full-time from home as effectively.[4]

In brief, we classify a surveyed worker as 'able to work from home' if they answer 'yes' to both questions above. We then compute measures of industry and occupation exposure by aggregating these survey responses across employees according to the industry and occupation codes which appear in the ATUS. In brief, our measure of industry exposure is

$$\text{Covid-19 Work Exposure}_I = 1 - \%\text{ of workers able to work from home}_I, \tag{1}$$

[2] Sandra L. Hofferth, Sarah M. Flood, Matthew Sobek and Daniel Backman. American Time Use Survey Data Extract Builder: Version 2.8 [dataset]. College Park, MD: University of Maryland and Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D060.V2.8

[3] For example, the Census' American Community Survey asks whether workers worked from home last week, which captures regular telecommuting behavior. According to the Census Bureau, around 4.3% of workers worked from home according to this measure in 2010 (Mateyka, Rapino, and Landivar, 2012).

[4] As further evidence of a sharper distinction, among households who provide non-missing replies to the question "What is the main reason why you work at home?", 60% of households who have worked days only from home are about twice as likely to list "job requires working at home", "reduce commuting time or expense", or "personal preference", which is significantly higher than the 31% frequency for other workers (t statistic on difference = 12.1). By way of contrast, in the group of workers who say that they have worked from home but have never worked days only from home, the most common answer to this question is "finish or catch up on work", which is selected 36% of the time, a significantly higher than the 14% of the time for those who have worked days from home (t=7.3).

which is computed as a weighted average of individual-level responses aggregated so as to be nationally representative using the BLS' person weights. If fewer than 5 survey respondents are directly employed in a given Census industry, we instead extrapolate using a weighted average of occupation-based measures.[5] Given that an individual's occupation likely provides a more accurate description of the types of tasks that a worker performs on a daily basis, we elect to use the occupation-based measure in person-level regressions below, though we obtain similar results if we use the industry-based measure. In general, we also find similar results if we use the more inclusive Alon et al. (2020) measure instead.

As most of our outcomes by industry use NAICS-based classifications, we crosswalk between the ATUS industry codes and NAICS industries.[6] We aggregate most outcomes, when available, to the 4-digit NAICS level given that the industry codes available in the IPUMS ATUS extract roughly correspond with this level of aggregation.

We find that most industries are highly exposed; the mean value of the measure is approximately 85%. Yet, there is considerable dispersion across NAICS industries—the cross-sectional standard deviation of our measure across 4-digit NAICS industries is approximately 17%. Clearly, some industries are more exposed than others. For example, General Merchandise Stores (NAICS 4523) and Meat Production (NAICS 3116) have an exposure measure of close to 1, since almost none of the workers in that industry report that they can work from home. By contrast, Software Publishers (NAICS 5112) is an industry in which the vast majority of workers report they can work from home, and accordingly has an exposure of just 0.38.

In addition, we perform some manual adjustments to the ATUS work exposure measure. For certain industries, we set their work from home exposure to 1, giving them "full exposure." These are largely industries that have been almost completely shut down and thus, even if some of their workers have the flexibility to be able to work from home in normal times, they cannot continue business as usual during lockdowns in a pandemic. These industries include: 4811 Scheduled Air Transportation, 5121 Motion Picture and Video Industries, 5151 Radio and Television Broadcasting, 5615 Travel Arrangement and Reservation Services, 7111 Performing Arts Companies, 7112 Spectator Sports, 7113 Promoters of Performing Arts, Sports, and Similar Events, 7114 Agents and Managers for Artists, Athletes, Entertainers, and Other Public Figures, 7131 Amusement Parks and Arcades.

[5] Specifically, we use data from the (considerably larger) 2016 American Community Survey to estimate the share of employees for each occupation by industry. We choose 2016 so that the occupation and industry codes coincide with those used in ATUS. American Community data are also taken from IPUMS: Steven Ruggles, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas and Matthew Sobek. IPUMS USA: Version 10.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D010.V10.0

[6] We make use of the crosswalks created by Evan Soltas, available here, which we update to use the 2017 NAICS code system.

1.2 Critical industries

While policy responses to the Covid-19 crisis have imposed severe restrictions on interactions between individuals, governments have found it necessary to make some exceptions, thus creating a need to classify industries as essential or non-essential. The Cybersecurity and Infrastructure Security Agency (CISA) provided guidelines to states about what kinds businesses should remain open. Keeping track of essential industries can enhance our analysis of work from home exposure because if a business is allowed to stay open, then it may be irrelevant if their workers can telecommute. We start with Pennsylvania's guidelines largely because they provide a list, based on the CISA guidance, of essential industries at the 4 digit NAICS (2017) level.[7] These industries primarily correspond to the production and sale of food and beverages; utilities; pharmacies; transportation; waste collection and disposal; and some healthcare and financial services.

While CISA's essential industry classification is a good place to start, we alter it for two basic reasons. First the classification of essential industries seems too coarse in certain cases. For instance, the NAICS code 4831, "Deep Sea, Coastal, and Great Lakes Water Transportation," is listed as essential by Pennsylvania. While some of the firms in this industry are shipping companies, the largest firms in this industry are cruise ships, which clearly have not been permitted to maintain business as usual. Second, the CISA list was somewhat inclusive in what types of industries were classified as providing critical infrastructure. We therefore removed from the critical list industries that faced severe restrictions to operating at a scale close to or even higher than pre-pandemic baselines. For example, restaurants, restaurant suppliers, and airlines have been permitted to remain open, however their patronage has declined dramatically due to quarantines and heavy restrictions on domestic and international passenger travel. While some restaurants remained open for curbside and/or takeout service, it is apparent that they were not classified as critical. Accordingly, we have also classified industries that are auxiliary to such industries (such as firms in NAICS code 4244 , Grocery and Related Product Merchant Wholesalers, which largely deliver food supplies to restaurants) as non-critical.

Given that we exclude the list of critical industries from the bulk of our empirical analysis, our choices of narrowing down the critical industry list can be viewed as conservative.[8] Appendix

[7]The CISA guidance is available here, while the full Pennsylvania list is available here

[8]As there are 311 industries represented by NAICS-4 codes, we will not to attempt to explain our justification by industry, but hope to provide some clarification on our thought process, which is primarily disciplined by the CISA guidance. In the case of manufacturing, for example, the CISA guidelines state that the following workers should be deemed critical: "Workers necessary for the manufacturing of metals (including steel and aluminum), industrial minerals, semiconductors, materials and products needed for medical supply chains and for supply chains associated with transportation, aerospace, energy, communications, information technology, food and agriculture, chemical manufacturing, nuclear facilities, wood products, commodities used as fuel for power generation facilities, the operation of dams, water and wastewater treatment, processing and reprocessing of solid waste, emergency services, and the defense industrial base... " (p. 17)

As steel and aluminum are mentioned explicitly and directly correspond to NAICS-4 codes 3312 ("Steel Product Manufacturing from Purchased Steel") and 3313 ("Alumina and Aluminum Production and Processing"), we have included those as critical. We also deemed Soap, Cleaning Compound, and Toilet Preparation Manufacturing (3256), Pharmaceutical and Medicine Manufacturing (3254), Plastics Product Manufacturing (3261), Agriculture,

Table A.1 provides the list of critical industries.

1.3 Validations using foot traffic data

We validate our critical/non-critical industry classification and remote work exposure measures using weekly foot traffic data from SafeGraph.[9] SafeGraph collects anonymized information on location activity from a large panel of mobile devices. For more than 5 million points of interest (POIs), we can observe aggregated daily activity of users in the panel. As activity exhibits strong within-week seasonal patterns, we aggregate the data to the weekly level. Given our focus on workers' ability to telecommute, we focus on visits to POIs that last for 4 hours or more, which we will refer to as "worker foot traffic".[10] For each 4-digit industry, we compare activity in week t with a baseline level of average activity: the mean of weekly activity over the period beginning with the week of January 6-12 and ending with the week of February 10-16. In the baseline period, the median 4-digit NAICS industry receives 18,705 worker visits per week, and the distribution of activity is highly right skewed, with the 90th, 95th and 99th percentiles having 560 thousand, 1.03 million, and 5.60 million hits respectively.

If our critical industry classification is accurate, we would expect to see a significantly smaller decline in foot traffic in critical industries than in non-critical ones —starting from the middle of March 2020 when Covid-19 awareness and state-mandated lockdowns went into effect. To test this hypothesis, we then aggregate foot traffic across all POIs to the 4-digit NAICS level so as to match our critical industry classification. Specifically, we estimate

$$\log\left(\frac{\text{Total Worker Foot Traffic in week t in Industry I}}{\text{Pre-period Average Worker Foot Traffic of Industry I}}\right) = a_t + \delta_t \,\text{Critical Industry}_I + \varepsilon_{I,t}. \tag{2}$$

When estimating (2), we weight observations by total industry employment, and, to minimize the effect of outliers, we winsorize these industry indices at the 1st and 99th percentiles.[11]

Figure 2 plots the results. Panel A reports average levels of our activity indices for critical and non-critical indices, respectively, along with 95% confidence intervals. Both sets of industries followed

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Construction, and Mining Machinery Manufacturing (3331), and Medical Equipment and Supplies Manufacturing (3391) as critical, as these clearly fall under the jurisdiction of the quoted CISA guideline. However, as most other manufacturing NAICS-4 codes represent industries that manufacture both products that would fit into the above categories as well as those that would not, we have largely chosen to designate the remainder of the manufacturing industries as non-critical.

[9] We are grateful to SafeGraph for making the data freely available to our research team and the broader community for Covid-19 related work. Further information about the data are available here. See also, e.g., Mongey et al. (2020) and Farboodi, Jarosch, and Shimer (2020) for additional applications of SafeGraph data to the study of Covid-19.

[10] Specifically, SafeGraph makes available data on number of visits by "bucketed dwell time", which captures the length of time that a device is at each POI. Consistent with the recommendations of SafeGraph researchers, we scale total weekly activity by a moving average the total number of devices in the panel over the prior week for each point of interest prior to aggregating.

[11] Some industries have very sparse coverage in the pre-period, so drop the approximately 5% industries with fewer than 30 average worker hits per week, though our results are insensitive to increasing this threshold or eliminating it entirely. Total NAICS4 employment is taken from the Census' 2017 Statistics of United States Businesses tables, available here

essentially identical trends in January and early February, then experienced a significant decline in foot traffic which dramatically accelerated in the middle of March of 2020. Though the Covid-19 pandemic affected almost all establishments, we can see that the decline is smaller for industries classified as critical. Panel B compares differences in traffic between the two industries by plotting the estimated coefficient β_t in equation (2) above. It shows that this decline was significantly smaller, by around 20%, for industries that we identified as providing critical infrastructure. We interpret these results as supporting our industry classification into 'critical' and 'non-critical' industries.

Our foot traffic data also permit a simple validation of our remote exposure measure. Our hypothesis is that, even in critical industries, workers would prefer to work from home to minimize their exposures to the disease to the extent that such activities are feasible. Whereas workers in non-critical industries are essentially prevented from going to their workplaces during the pandemic, the decision to telework is more discretionary in nature for workers in critical industries. Accordingly, we would expect to see larger declines in worker foot traffic (i.e. increased telecommuting) in critical industries, in which workers are more easily able to telework. To test this premise, we estimate the following specification for critical (panel C) and non-critical (panel D) industries,

$$\log\left(\frac{\text{Total Worker Foot Traffic in week t in Industry I}}{\text{Pre-period Average Worker Foot Traffic of Industry I}}\right) = c_t + \gamma_t \,\text{Covid Exposure}_I + \varepsilon_{I,t}. \quad (3)$$

where our prediction is that $\gamma_t > 0$ since workers in critical, high exposure industries will be more likely to go to work relative to their counterparts who can telecommute more easily. Panel C provides strong evidence in support of this hypothesis: a 1% increase in the fraction of workers who cannot work remotely is associated with between 1-1.5% higher foot traffic throughout the month of April. In contrast, exposure is not correlated with changes in foot traffic in non-critical industries, which is consistent with the non-critical distinction requiring all workers to work remotely regardless of feasibility constraints.

1.4 Heterogeneity in work exposure

Figure 1 plots the distribution of the Covid-19 work exposure measure across NAICS4 industries. We report results separately for critical and non-critical industries. We note that most industries have relatively high values of Covid-19 work exposure; the average is equal to approximately 0.85 for critical and 0.87 for non-critical industries. More importantly, however, we see there is considerable dispersion in our measure—the cross-sectional standard deviation is approximately 17%. The bulk of our paper explores the extent to which these cross-sectional differences are predictive of differential economic outcomes during the pandemic.

Table 1 illustrates how our industry Covid-19 work exposure measure is related to firm characteristics; due to data availability, we restrict attention to publicly-listed firms. Panel A shows results for all industries, while Panel B restricts to the non-critical industry sub-sample. Two patterns stand out. First, we see that firms in the high-exposure category tend to be larger. For instance, focusing on the sub-sample of non-critical industries, the median firm in the top quartile of the Covid-19 work exposure measure has 4.9 thousand employees; by comparison, the median firm in the bottom quartile has 1.5 thousand employees. Second, there is some evidence that firms in the least exposed industries have more intangibles than firms in the most exposed industries: these firms have higher market valuations (median Tobin's Q of 2.3 for the most exposed vs 1.3 for the least exposed); have lower ratios of physical capital (PPE) to book assets (0.16 vs 0.58); and spend significantly more on R&D and SG&A than firms in the most exposed industries.[12] This is consistent with the view that firms with more intangibles have more jobs that can be done remotely than firms that rely more on physical assets. Last, firms in the most exposed industries are more profitable in terms of bottom-line accounting measures (return-on-assets) but this difference is driven by higher spending on intangibles and/or fixed costs by firms in the least exposed industries.

2 Covid-19 Work Exposure and Economic Performance

So far, we have constructed a measure of exposure to Covid-19 work disruptions using data from the 2017 and 2018 ATUS. Here, we explore the extent to which this Covid-19 work exposure measure is able to predict differences in economic performance across industries and individual workers. Our outcome variables include data on employment outcomes at the industry and worker level, as well as forward-looking variables that are indicative of future economic performance—analyst forecasts and default probabilities.

Each of these variables has distinct advantages and disadvantages. Data from financial markets and financial analysts are forward-looking but are only available for public firms, which may be less exposed to supply-side disruptions than smaller private firms. Employment data are more representative of the universe of firms but are only available with a lag and may not accurately reflect outcomes for firm owners.

2.1 Employment

We begin by exploring the extent to which our measure of production disruption due to the pandemic can predict differences in employment declines across industries. We use two sources for data on employment.

First, we focus on aggregated employment data from the Bureau of Labor Statistics (BLS). Each month, the BLS aggregates data from large surveys of firms' establishments in order to construct estimates of total employment by industry. We make use of data from Table B-1A of the April

[12] Corrado, Hulten, and Sichel (2009) and Eisfeldt and Papanikolaou (2013) argue that higher SG&A expenditures are associated with higher investment in intangibles. That said, Eisfeldt and Papanikolaou (2013) focus on within-industry differences, whereas these results reflect between-industry patterns. As such, these differences in SG&A could also reflect differences in operating leverage (importance of fixed costs) or differences in accounting practices.

employment report, which provides estimates of seasonally-adjusted employment at the 4-digit NAICS level for the vast majority of non-agricultural industries in the US economy.[13]

We estimate the following specification

$$\text{Employment Growth}_I = a + \beta \, \text{Covid-19 Work Exposure}_I + \varepsilon_I. \tag{4}$$

Here, the unit of observation is a 4-digit NAICS industry and the outcome variable is employment growth. We examine both monthly but also annual changes—that is, between either March 2020 or April 2019 and April 2020. Since the size of these industries varies greatly, depending on the specification, we also present results in which we weight industries using total employment as of the baseline period used in each growth rate. Last, we report results either using the full sample, or by excluding the list of critical industries in Table A.1.

Table 2 and Figure 3 present our results. Examining columns (1) through (8) of the table, we see an economically and statistically significant correlation between our exposure measure and industry-wide declines in employment that is robust across different specifications. In particular, a one-standard deviation increase in our Covid-19 work exposure measure is associated with a 5.6 to 10.3 percent greater decline in employment. The magnitudes are comparable when we focus on monthly or annual growth rates and are larger when we exclude critical industries and weigh industries by their total employment. These magnitudes are quite significant and comparable to either the average decline in employment during this period (14 percent) or the cross-sectional standard deviation (17 percent). In panel B, we also report the differences in average employment growth rates between industries which we classify as critical vs non-critical. On an employment-weighted basis, monthly declines in employment are more than 5 times larger in non-critical industries (-22.5%) relative to critical ones (-4.08%).

Figure 4, Panel A, provides a more aggregated summary of the relationship between our exposure measure and BLS employment year-on-year employment growth. Specifically, we aggregate across non-critical industries by major 2-digit NAICS sector. Even at this level of aggregation, one can observe a strong relationship between exposure and changes in employment. Unsurprisingly, the three hardest-hit sectors are retail, hotels, and entertainment, which are also the three most highly exposed sectors according to our measure.

2.2 Revisions in Revenue Forecasts

We next examine the ability of our measure to predict revisions in analyst forecasts regarding the economic performance of these industries. Specifically, we use consensus forecasts of firms' revenues over various horizons from Capital IQ as of various points in time. We begin by comparing the change in revenue forecasts for the same accounting period (e.g., 2020Q2) across two points in time,

[13] Data were accessed here.

February 14 and May 15, 2020. Later, we illustrate how these forecasts evolved on a weekly basis.

We focus on forecast horizons up to three years ahead, that is, Q2 through Q4 of 2020, and full year forecasts for 2020–22. We use the Capital IQ 'consensus forecast.' To minimize measurement error, we require that each firm has at least 3 individual forecasts. Due to this restriction, as well as the fact that underlying forecasts are less sparsely populated at longer horizons, we lose some industries for longer run forecasts, especially 2022. For each firm f in the sample, we compute the percent change in revenue forecast from February to May 2020,

$$\frac{\text{Revenue forecast for Period } \tau \text{, as of May } 2020_f}{\text{Revenue forecast forPeriod } \tau \text{, as of February } 2020_f} - 1. \tag{5}$$

For purposes of these regressions, we winsorize firm-level measures at the 1st and 99th percentiles, then aggregate the non-missing firm-level revenue forecasts to the 4-digit NAICS level, weighted by the corresponding level of the firms' February 2020 forecasts for the same period,

$$\text{Forecast Revision}_I^\tau = \frac{\sum_{f \in I} \text{Revenue forecast for Period } \tau \text{, as of May } 2020_f}{\sum_{f \in I} \text{Revenue forecast forPeriod } \tau \text{, as of February } 2020_f} - 1. \tag{6}$$

We re-estimate equation (10), but we now replace the dependent variable with the revision in analyst forecasts in (6)

$$\text{Forecast Revision}_I^\tau = a_\tau + \beta_\tau \text{ Covid-19 Work Exposure}_i + \varepsilon_i^\tau. \tag{7}$$

Our dependent variable is the revision in analysts' revenue forecasts for period τ between February and May 2020, aggregated to industry i. To conserve space, we focus our preferred specification in which we restrict the sample to non-critical industries and weigh observations by the number of Compustat employees in each industry; using equal weights or weighting by the number of firms leads to quantitatively similar results. Standard errors are robust to heteroskedasticity (White, 1980).

Columns (2) to (7) of Table 4 present our findings. Column (2) shows the effect of the exposure measure on revenue forecast revisions for Q2 2020. A one-standard deviation increase in the exposure measure is associated with a 7.7 percent decline in analysts' revenue forecasts. Importantly, the effect is quite persistent, though the magnitudes do decline with the forecast horizon τ, as we can see from comparing the magnitudes across columns. Figure 7 plots the estimated coefficients as a function of the forecast horizon τ. We see that financial analysts expect the direct economic cost of the pandemic to subside significantly over the course of 2020: a one-standard deviation increase in the exposure measure is associated with a 3 percent decline in revenue for Q3, while the estimate for Q4 2020 is equal to -1.4 percent. The overall estimate for 2020 is equal to 2.6 percent. Extending our analysis to 2021 and 2022, we note that our estimates are significantly weaker at 2 and 1.5 percent, respectively—though still statistically significant—suggesting that analysts expect the costs of these supply side disruptions to persist for several years. Figures 4 and 6 provide scatter plots for non-critical industries aggregated by major sector and across all 4-digit industries, respectively.

In Panel B, we also report industry-level averages of these revenue forecasts for critical versus non-critical industries (weighted by 2019 employment levels from Compustat). We note that projected declines are roughly three times larger for firms in non-critical industries relative to their counterparts critical ones. In both cases, the largest declines in revenue are expected for 2020Q2 (-26% and -8% for non-critical and critical, respectively), though revenue forecasts suggest that non-critical industries are expected to experience substantial long-run declines in output. In particular, non-critical industries are projected to experience revenue declines of 10 percent and 8 percent in 2021 and 2022, respectively.[14]

2.3 Default Probabilities

So far, we have seen that our Covid-19 work exposure measure predicts declines in both employment declines as well as expected revenue across industries. We next examine another forward-looking measure, expected probabilities of default.

We obtain estimates of default probabilities from the Risk Management Institute (RMI) of the National University of Singapore. RMI generates forward-looking default probabilities for issuers on a daily basis for maturities of 1, 3, 6, 12, and 24 months ahead using the reduced form forward intensity model of Duan, Sun, and Wang (2012). These measures have been shown to work well in forecasting applications and are available for a very wide array of firms (over 70,000 publicly listed firms worldwide).[15] We next compute the first difference of the default probability over our the May–Feb 2020 period and aggregate these default probabilities at the industry level (4-digit NAICS) by averaging across firms (weighted by employment).

We estimate the following specification,

$$\text{Default Probability}_I^\tau = a_\tau + \beta_\tau \,\text{Covid-19 Work Exposure}_I + \varepsilon_i^\tau. \tag{8}$$

The outcome variable is the industry-level probability of default over the next τ months. As before, we restrict the sample to non-critical industries and weigh observations by the number of employees in each industry.

Table 5 and Figure 8 present the results. Examining Table 5, we see that differences in our Covid-19 work exposure measure are associated with increased probabilities of default. This correlation is both statistically and economically significant and is monotonically increasing in the forecast horizon τ. For instance, a one-standard deviation increase in our measure is associated with a

[14] See, e.g., Landier and Thesmar (2020) and Barrero et al. (2020) for related evidence on projected aggregate declines.

[15] For example, Gallagher, Schmidt, Timmermann, and Wermers (2020) use these probability estimates to study changes in portfolio risk of international portfolios of securities owned by US money market funds, and illustrate that the default probabilities closely track CDS spreads. For additional details on the database, see here.

0.22 percentage point increase in the probability of default over the next 6 months and a 0.44 percentage point increase over the next 2 years. Given that the average probability of default over these horizons is 0.26 percent and 1.38 percent, respectively, these magnitudes are quite substantial. Consistent with earlier evidence, we also observe that these increases in default risk are considerably higher for non-critical industries relative to critical industries.

2.4 Evidence Based on Firm Surveys

Last, in this section we provide additional survey-based evidence that link firms' experience during the pandemic to our Covid-19 work exposure measure. We use the Small Business Pulse Survey (SBPS), which was recently introduced by the Census Bureau to provide timely information on how firms are impacted by the crisis. Each week, the Census sends an electronic survey to a very large sample of small businesses and reports statistics which are aggregated across respondents by 3-digit NAICS sector.[16]

The SBPS contains responses to several questions on whether the firm is experiencing material hardship during the pandemic. We assume that a firm is experiencing a Major Disruption if it responds to the question "Overall, how has business been affected by the COVID-19 pandemic?" with an answer of "Large Negative Effect". At the mean level of exposure, 49% of firms answer in the affirmative. Next, we consider whether a firm has reduced its employee headcount or hours in the last week, which is captured by "Yes, decreased" answers to the questions "In the last week, did this business have a change in the number of paid employees?" and "In the last week, did this business have a change in the total number of hours worked by paid employees?", respectively. We code a firm as having missed payments if it responds in the affirmative to the question of whether, "Since March 13, 2020, has this business missed any other scheduled payments, not including loans? Examples of other scheduled payments include rent, utilities, and payroll." Last, we determine the firm's liquidity position based on their answer to the question "How would you describe the current availability of cash on hand for this business, including any financial assistance or loans? Currently, cash on hand will cover X weeks." We thus compute the fraction of firms that report that they do not have enough cash to cover at least 4 weeks of business operations. We average survey responses across the first six waves of the survey, which corresponds with data collected from April 26 through June 6, 2020.

Table 6 and Figure 10 summarize the relationship between our Covid-19 work exposure measure and these self-reported measures of hardship. In particular, Columns (1) to (5) of Table 6 report univariate regressions, weighted by employment, of the fraction in percentage points responding in the affirmative on our exposure measure. We de-mean the exposure measure prior to running the regression, so that the constant may be interpreted as the average response for a firm with the

[16]The target population is small businesses with fewer than 499 employees. Multi-establishment firms are excluded from the sampling frame. For additional details, see Buffington, Dennis, Dinlersoz, Foster, Klimek, et al. (2020). The data is available here.

average level of exposure (about 86%). Panel A reports these responses for all industries included in the sampling frame, whereas panel B subsets to our list of non-critical industries only. For brevity, we focus on estimates for non-critical industries in our discussion, though estimates are qualitatively similar for the full sample.

In sum, our Covid-19 work exposure measure is significantly correlated with these hardship measures. Examining Columns (1) to (5) of Table 6, we see that a one standard deviation increase in our exposure measure is associated with a 9.4 percentage point increase in the probability the firm is experiencing a major disruption in operations; 5.7 and 4.0 percentage point increases in the likelihood of reducing headcount and payroll, respectively; a 5.9 percentage point increase in the probability of missing payments; and a 4.3 percentage point increase in the likelihood of having insufficient liquidity.

Panels A through E of Figure 10 illustrate these results graphically. These figures show nonparametric evidence on the relationship between exposure and survey responses via binned scatter plots, in which we separate non-critical industries into 10 bins, then report for each bin the (employment-weighted) means of exposure and the fraction of survey respondents answering yes to each question. These plots confirm the regression results and illustrate that the strong relationship between exposure and measures of economic hardship is not driven by a small set of outliers.

3 Covid-19 and Income Inequality

The recent availability of CPS data allows us to explore outcomes at the level of individual workers. The advantage of doing so is twofold. First, by observing the characteristics of individual workers we can control for some variables that may be correlated with our Covid-19 work exposure. For instance, workers that can work remotely tend to be in white collar occupations (see e.g., Dingel and Neiman, 2020). By including controls for workers' level of education, or past earnings, we can ensure that we are comparing otherwise similar workers. Further, analyzing outcomes for individual workers, and how these outcomes vary with worker characteristics, reveals a fuller picture of the effects of the Covid-19 on heterogeneity in worker outcomes.

We use the April version of the Current Population Survey (CPS) which contains employment information for individual workers.[17] We restrict the sample to adults of working age (25 to 60 years) that are present in the March 2020 survey and who report that they were "at work last week" as of March 2020. Our sample contains 23,984 workers. In April of 2020, 19,664 out of these workers report they are at work; 2,144 report they are out of a job; while 1,257 report they have a job but

[17] There are some possible selection issues. IPUMS notes that: "Interviews for April were conducted exclusively by phone. The two Census Bureau call centers that usually assist with the collection of CPS data remained closed. Response rates continued to be low in April, over 10 percentage points below the average (see below). Response rates continued to be particularly low among rotation groups one and five who would have normally received a visit from the enumerator. Month-in-sample one and five response rates were similar to those same groups in March. Additionally, those households that entered the survey for the first time in March had a similarly low response rate for their second interview in April."

were not at work last week. We include the first and last groups in our definition of employment for our regressions below.

We impose one other substantial restriction of the sample. As of the start of the year, the BLS changed its coding of occupations relative to prior years, and a crosswalk between the older vintage of occupation codes from ATUS and the newer codes in the 2020 CPS has not yet been developed. In part due to this technical reason and also given that several researchers have already documented a disproportionate increase in unemployment for lower income workers, we restrict attention to the subsample of workers who appear in the March/April 2020 core CPS and March 2019 Annual Social and Economic (ASEC) CPS surveys. This enables us to construct controls for an individual's prior income and, motivated by evidence on potentially concentrated adverse effects for small businesses, firm size. For each worker, we assign an exposure measure based on her March 2019 occupation which is equal to one minus the fraction of ATUS respondents (weighted using the ATUS sampling weights) who had worked a full day from home.[18]

We estimate the following specification

$$\text{NotEmployed}_i = a + \beta \, \text{Covid-19 Work Exposure}_i + c \, Z_i + \varepsilon_i. \tag{9}$$

Our main outcome variable is a dummy variable that takes the value of 1 if the worker was not 'at work last week' in the April 2020 CPS survey, which therefore includes both unemployed and furloughed workers. For ease of interpretation, we multiply the dependent variable by 100 to express probabilities in percentage points in tables and figures.

Since the CPS contains information on workers' occupation, we use the occupation-level measure of our Covid-19 work exposure rather than the industry aggregate—though using industry aggregates produces largely comparable results. Depending on the specification, the vector of worker-level controls and interaction terms Z_i includes gender dummies; college education; whether the worker has children younger than 14 years old; education (a college graduate dummy); worker age; worker earnings as of 2019 (quartile dummies); and firm size dummies. We cluster the standard errors by occupation and industry (using Census codes). Table 3 shows results.

Examining Table 3, several facts stand out. First, as we see in the first three rows of the table, workers in occupations that are less able to work remotely (higher Covid-19 work exposure) are more likely to stop working. These effects are not absorbed by worker characteristics—as we see in columns (2) and (3)—suggesting that our Covid-19 work exposure measure is not simply capturing differences in the composition of the work force. Further, the point estimates are somewhat larger for non-critical industries relative to critical industries. Focusing on column (3)—which includes controls for worker gender, age, education, prior earnings, and firm size—a one-standard deviation increase in our Covid-19 work exposure measure is associated with a 4.5 percentage point increase in the

[18]Note that we also assigned an alternative measure based on each worker's March 2020 industry and obtain similar results.

probability of a worker in a non-critical industry being without employment in April 2020, compared to a 1.0 percentage point increase for a worker in a critical industry, that is however statistically not significantly different from zero. Moreover, relative to workers in non-critical industries with similar characteristics, employees in critical industries are 8 percentage points less likely to remain employed. Hence, in the remainder of the paper, we restrict attention to non-critical industries.

One potential concern with these results is that they could simply reflect differential employment trends in white-collar versus blue-collar occupations. Column (4) of Table 3 performs a placebo exercise, in which we repeat the analysis for the February CPS sample—well before the effects of the pandemic became apparent. Examining the results we note that none of the coefficients of interest are statistically different from zero.

We next allow the coefficient β on the Covid-19 work exposure measure in equation (9) to vary with worker characteristics Z_i. In all specifications with interactions, we include dummies for all levels of the categorical variable of interest as controls. Doing so reveals how the employment status of different workers varies in response to the same level of work disruption due to Covid-19.[19]

Figure 5 summarizes our findings. In Panel A of the figure, we see an economically and statistically significant difference in how the employment status of workers of different income levels is related to our Covid-19 exposure measure. A one-standard deviation increase in our work exposure measure is associated with a 9.2 percentage point increase in the likelihood of non-employment for workers at the bottom quartile of the earnings distribution—compared to just a 1.6 percentage point increase for workers in the top quartile. The fact that we see such a differential response of employment status to the feasibility of remote work for employees with different earnings levels has several interpretations. One possibility is that firms try to retain their most able—and highest paid—employees and reduce employment for workers of lower skill levels first. Moreover, in addition to these differences in slope coefficients, low income workers tend to be less able to work remotely: average exposure is 1.0%, 3.2%, and 7.7% higher for workers in quartile 1 relative to workers in quartiles 2, 3, and 4, respectively.

Another possibility is that these responses reflect differences in age or the gender pay gap. Panel B of the Figure shows that there is some evidence that the employment status of younger workers responds more by approximately a factor of two than older workers to Covid-19 work disruptions, but the coefficients are imprecisely estimated so the difference is not statistically different from zero. Panels C and D condition on gender as well as college attainment and whether or not the household has at least one child under the age of 14. In both cases, we see that estimated sensitivities for women are large relative to men, though these differences are not always statistically significant. Workers without college degrees have higher estimated coefficients. In panel D, we observe that men with young children who work in non-critical industries have smaller coefficients than men

[19]In additional specifications, we verify that many of these patterns persist even if we include occupation and/or industry fixed effects, implying that we can detect similar differences even within occupations/industries. These results are suppressed for brevity and are available upon request.

without young children; the opposite appears to be the case for women with young children. The 7.7 percentage point difference in coefficients between men and women with young children is highly significant (t=3.4).[20] Panel E shows that these gender differences do not merely reflect the gender pay gap. More importantly though, Panel E reveals that the employment status of female workers is more sensitive to work disruptions than the status of male workers, for all income levels. Panel F shows that the workers most adversely affected by the work disruptions due to Covid-19 are female workers with young children and without a college degree. For this group, a one standard deviation increase in our Covid-19 work exposure measure is associated with about a 15 percentage point increase in non-employment—which is three times higher than the average response among all workers.

In sum, we find that our Covid-19 work exposure measure is an economically significant predictor of employment. Workers in occupations that cannot work remotely are significantly more likely to have lost their employment status in April 2020. This correlation is evident both in cross-industry comparisons and in individual worker regressions.

4 Stock Market and the Pandemic

So far, we have seen that differences in our Covid-19 work exposure measure are correlated with differences in real economic outcomes across firms—both forecasts and realizations. Here, we extend our analysis to stock return data. This analysis complements the previous section in several ways and sheds some light on the apparent disconnect between the behavior of the stock market versus the behavior of the real economy in 2020.

4.1 Stock market performance during the first peak of the pandemic

So far, we have seen that differences in our Covid-19 work exposure measure are correlated with differences in analyst forecasts of revenue growth and default probabilities. Though forward looking, both of these measures are somewhat subjective and may not necessarily reflect the 'average' beliefs in the economy. Our next outcome variable partly addresses this concern, as it focuses on differences in stock market valuations across industries.

We use data on stock returns from the *Compustat Daily Update* database to holding period returns over various horizons. We restrict attention to common stocks of firms that have headquarters in the United States and are traded on NYSE, AMEX, or NASDAQ. We eliminate financial and real estate firms (NAICS codes 52 and 53).[21] Almost all of the industries performed negatively during

[20] This gap remains sizable at 5.5 percentage points when we absorb occupation fixed effects.

[21] We also exclude firms in the education sectors (6111–6114), because the remote exposures of employees of the listed firms employed in these sectors are likely to be quite different from those employed in the non-profit/government enterprises which comprise the vast majority of employment in these sectors. Likewise, we exclude fast food restaurants (NAICS 722513) from the sample, as their exposures are likely to be quite different from other firms in the restaurant industry.

this period: the cross-sectional average decline is equal to approximately 26 percent. Yet, there is considerable cross-industry dispersion—the cross-sectional standard deviation is approximately equal to 18 percent. A select few industries experienced price appreciation: firms in the grocery store industry (NAICS 4451) saw a 21 percent increase in stock market values; firms in electronic shopping (NAICS 4541) appreciated by approximately 13 percent. Others such as airlines (NAICS 4811) experienced stock market declines of more than 65 percent.

Figure 9 illustrates our main results graphically via a scatter plot of our exposure measure versus the stock market performance of these industries. Essential industries are marked in red, while the trend line is estimated in the sample of non-essential industries. We note some significant outliers that do not fit the line. For example, NAICS code 5414 corresponds to interior designers; these workers can work remotely in normal times, but likely face significant impairments to implementing these designs in the current environment.

We relate differences in our work exposure measure to differences in cumulative stock market performance using the following specification,

$$\text{Stock Returns}_i = a + \beta \, \text{Covid-19 Work Exposure}_i + \varepsilon_i \tag{10}$$

The dependent variable corresponds to cumulative stock returns from February 14th through May 15, 2020. As before, we restrict the sample to non-critical industries. To ensure that our results are not driven by small industries with high idiosyncratic volatility, we estimate (10) using weighted least squares—where we weigh observations by the total number of employees (across firms in our Compustat sample) in each industry. Weighting by the number of firms in each industry leads to quantitatively similar findings. Standard errors are robust to heteroskedasticity (White, 1980).

Column (1) of Table 4 present our estimates. Examining the table, we see that our industry exposure measure is economically and statistically significant in accounting for differences in the economic performance across industries. The magnitudes are considerable: a one-standard deviation increase in the lockdown measure is associated with a 6.8 percent decline in stock prices during this period. Given that the cross-sectional standard deviation in industries' stock market performance during this period is approximately 16.6 percent, our measure captures a significant share of the overall dispersion. Figures 4 and 9 provide scatter plots for non-critical industries aggregated by major sector and across all 4-digit industries, respectively. In Panel B, we also note that stock market declines are considerably larger (26%) in non-critical industries relative to critical ones (8%).

In sum, we find that a measure of disruption exposure constructed with pre-2019 data is a statistically significant predictor of cross-industry heterogeneity in returns during the Covid-19 pandemic. That said, however, these estimates are somewhat at odds with the impact on stock returns we discuss above. Specifically, as we compare Columns (1) through (8) of Table 4, we see that a one-standard deviation increase is associated with 6.7 percent decline in stock prices, whereas the expected decline in revenues over 2020 and beyond is much smaller and short-lived. In reconciling these differences, a few possibilities emerge. First, firms profits may be substantially more affected than revenues; second, the differential stock return performance could also driven by differential increases in systematic risk during this period. After all, the January to May period of 2020 is a period of increased uncertainty (see e.g., Baker, Bloom, Davis, and Terry, 2020).

4.2 Real-time estimates of the supply-side disruption

In our analysis so far, we have developed a measure of industry exposure to production disruptions due to Covid and shown that heterogeneity in risk exposures is associated with cross-industry differences in economic performance during the pandemic period. Our analysis was essentially cross-sectional in nature as we focused on cumulative outcomes during the entirety of the pandemic period. However, our measure can also be used to construct a real-time indicator of news associated with these production disruptions. To do so, we exploit the high-frequency information in data from the financial markets.

In particular, we re-estimate equation (10) for the subsample of non-critical industries, while allowing the slope coefficient to vary over time,

$$\text{Stock Returns}_{i,t} = a + \beta_t \,\text{Covid-19 Work Exposure}_i + \varepsilon_{i,t}. \tag{11}$$

The realized time-series of the slope estimates β_t have a portfolio return interpretation. That is, they are a noisy estimate of the 'Covid-19 return factor,' the source of common variation in returns related to the production disruptions stemming from the pandemic (see, e.g. Fama and MacBeth, 1973; Cochrane, 2009, for more details). Intuitively, this factor is a long-short portfolio of industries based on their disruption exposure: it loads positively on industries in which a lower fraction of workers report that they can telecommute, while loading negatively on industries in which a higher fraction of workers report that they can work remotely. Specifically, the return on the Covid-19 factor can be expressed as

$$\hat{\beta}_t = \sum_i w_i (R_{i,t} - \bar{R}_t^{emp}), \text{ where } \bar{R}_t^{emp} \equiv \frac{1}{N} \sum_{i=1}^{N} \frac{emp_{i,0}}{\overline{emp}_0} R_{i,t} \equiv \sum_{i=1}^{n} e_i R_{i,t}, \tag{12}$$

where e_i is the employment share of industry i. The portfolio weight industry i receives in the Covid-19 portfolio can be written as

$$w_i = \frac{e_i \left[X_i - \sum_{l=1}^{N} e_l X_l\right]}{\sum_{j=1}^{N} e_j \left[X_j - \sum_{k=1}^{N} e_k X_k\right]^2} = \frac{e_i \left[X_i - \bar{X}^{emp}\right]}{\sum_{j=1}^{N} e_j \left[X_j - \bar{X}^{emp}\right]^2}, \tag{13}$$

where X_i is our (predetermined) measure of exposure for firm i, so the portfolio holds long positions in stocks with exposure above the employment-weighted average exposure and short positions otherwise.

Figure 11 summarizes how these portfolio weights vary across different broad sectors (2-digit NAICS codes). The portfolio overweights industries whose workers can perform their tasks from home, and underweight sectors where workers cannot work remotely. Consistent with the discussion so far, we see that firms in retail trade, and accomodation and food services receive large positive weights; by contrast, firms in professional services and information technologies receive negative weights. Appendix Table A.2 contains the full list of weights on NAICS 4-digit industries.

Figure 12 plots these factor realizations in blue, along with returns on the market portfolio in red. First, we note that the correlation between our factor and the market portfolio in the three months before the pandemic period is significantly negative (approximately -0.4), which suggests that the industries most exposed to the Covid pandemic are industries with low systematic risk during normal times. However, given the dominance of Covid-related news during this period, the correlation with the market during the pandemic period is positive, though modest (it ranges from 0.1 to 0.3 depending on how the factor is constructed). Further, we see in Figure 12 that extreme daily realizations of our factor are associated with significant news about the pandemic.

In brief, we see that realizations of our 'Covid-19 factor' largely track the unfolding of news related to the pandemic. As of May 15 2020, this long-short portfolio had lost roughly 50 percent of its value since the beginning of the year, compared to 10 percent for the broad market index. This pattern supports the view that Covid-19 is primarily a reallocation shock as not all sectors were symmetrically affected, which also echoes the views in Barrero et al. (2020). These results speak to how investors could construct an investment strategy that could significantly hedge future Covid-19 related uncertainty. They could do so by taking a short position in our Covid-19 factor, which would involve taking the opposite position to the one described in Appendix Table A.2 .

Figure 13 presents industry returns by varying levels of exposure. Specifically, we form five value-weighted portfolios using information on exposure, critical industry status, and market cap. The first portfolio includes all critical industries, while the remaining four sort non-critical firms into four groups according to our remote exposure measure. We choose the breakpoints so that approximately 25% of the market value of non-critical firms is associated with each bin as of February 14, 2020. Panel A shows cumulative returns since the start of 2020. The solid black line also plots the value-weighted return of all companies which were included in our sample, and panel B shows how stocks have performed relative to this market index since February 14.[22] During the last two weeks of February, we see that critical industries performed modestly better than other industries, and we do not see major differences across the Covid exposure-sorted portfolios. However, beginning in early March and lasting throughout the crisis, we observe substantial differences in

[22]Recall from section 4.1 that a small number of industries were dropped from the analysis. We exclude them from our market index construction as well; that said, our market index closely tracks movements in other broad market indices. More specifically, Panel B is computed as the difference between the cumulative return on each portfolio since February 14th and the market cumulative return over the same period.

cumulative returns between firms with different levels of exposure, with returns being inversely related to exposure. The spreads between the most exposed and least exposed industries peak at around 25% in mid-March and only shrink slightly into early June.

Last, we also examine the real-time response of our two other forward-looking variables—revisions in analyst forecasts and estimated default probabilities. Figures 14 and 15 summarize our findings. Similar to our stock return evidence above, we see an increased divergence in revenue forecasts and expected default probabilities across high- and low-Covid 19 work exposure industries by the end of March and beginning of April 2020. Comparing the two figures, we see that default probabilities appear to respond a bit earlier than analyst revenue forecasts, and they seem to recover somewhat from their peaks by the end of April. That said, these differences could simply be due to the fact that analyst forecasts are released with some delay.

4.3 The apparent disconnect between the stock market and the economy

In this section, we make use of our exposure measure and outcome measures in order to shed light on one of the more surprising outcomes which has obtained in the early stages in the pandemic-induced recession. Despite the fact that many measures of real activity, including initial claims for unemployment and the employment-population ratio, have reached uncharted territory, the stock market quickly rebounded from its March lows. Numerous explanations have been put forward for this. First, the most severe effects of the pandemic recession on overall activity are likely to be fairly transitory in nature, whereas stock prices capitalize the entire present discounted value of future profits of listed firms. Second, both short and long term interest rates have declined following large amounts of fiscal and monetary stimulus, a force which pushes valuations higher ceteris paribus. In addition, listed companies tend to be larger, and small firms are thought to be more exposed to the fallout from the virus. For instance, larger firms have better access to capital markets, and fixed compliance costs associated with Covid are likely easier to absorb for larger firms.

We consider a very simple and complementary explanation to those proposed above. Specifically, the industrial composition of the stock market is not fully representative of the broader (listed and non-listed) economy. In the vast majority of cases, a market index such as the S&P 500 weights each of its constituents proportionately with its market capitalization. There are well-understood patterns of which types of firms find it most valuable to list publicly (Doidge, Karolyi, and Stulz, 2017), and publicly listed firms now comprise a smaller share of aggregate employment relative to the past (Schlingemann and Stulz, 2020). For instance, tech firms are substantially over-represented in market indices relative to their share of overall employment in the US economy. Moreover, as is indeed the case for the tech sector overall, many of these over-represented sectors turn out to have a larger share of employees who are able to work from home.

We investigate this possibility systematically by considering two different approaches to aggregating our exposure measure, as well as measures of market values and operating activity, across industries. Via one approach, we compute weighted averages using each industry's share of market capitalization as of Feburary 14, 2020. As an alternative intended to more accurately reflect the industry mix of the broader nonfinancial corporate sector, we construct industry weights 4-digit NAICS employment totals as of 2017 from the Census Bureau's Statistics of US Businesses database.[23] Using a simple regression approach, we construct a statistical test for the difference between the market value-weighted and employment means. Specifically, we append two copies of the dataset, where one copy is associated with each set of weights, then run a pooled (weighted) regression of each industry outcome on a dummy variable which equals 1 when we use value weights and 0 when we use employment weights with standard errors clustered at the industry level. We then report the t-statistic on the null hypothesis that this dummy equals zero, which would imply that the two weighted means are identical.

These two different weighting schemes provide very different pictures of the overall exposure of the set of industries that include at least one listed firm. When we weigh industries according to their market values, average Covid-19 exposure is only 66%, which is about 21 percentage points higher ($t = 4.8$) than the 87% mean which obtains when we instead use employment weights. In brief, the aggregate stock market is considerably less exposed to the supply side shock; moreover, some larger companies (e.g., Amazon.com) have substantially benefitted from the resulting sectoral reallocations it has induced. As an example, the employment share for the Information sector (NAICS 51) is only 3.5%, whereas this sector comprised 24% of the market cap of listed firms as of February 2020. Moreover, even within tech, the composition of firms is tilted towards less-exposed industries; employment and market cap-weighted exposures are 56% and 43%, respectively. A similar pattern emerges for Manufacturing industries (NAICS 31-33), which comprise about 48% of the total market cap of nonfinancial industries included in our analysis (versus only about 11% of employment). While the employment-weighed average exposure is 85%, the market cap-weighted exposure of listed firms in these industries is 66%.

Table 7 and Figure 16 report related weighted means for cumulative stock market returns and analysts' forecast revisions for revenue at various horizons measured at different dates during the pandemic. Different rows in the table correspond with different dates and different columns tabulate different outcome measures. We also report the difference between the two means and a t-statistic for the null hypothesis that the two means are identical. Figure 16 presents these same outcomes at a weekly frequency from Feburary 21st onwards. As of March 20th, near the market trough, the employment-weighted index is down by 39%, which is about 7.4 percentage points more than the market-cap weighted index. This gap, which is statistically significant at all dates, widens a bit more to about 10 percentage points at the later horizons. We observe a similar picture for revenue forecast

[23] Note that these are buy-and-hold indices. If a stock is delisted, we assume proceeds are held in cash, which is virtually identical to investing in a short term Treasury bill rate given short term interest rates were approximately at the zero lower bound throughout this period. Note that, as before, we exclude finance, insurance, and real estate from these estimates. As both of these sectors experienced larger market declines relative to overall market indices, our value-weighted index actually shows an even stronger rebound relative to others such as the S&P 500 index.

revisions (after allowing for some potential lag for analysts to update them). Across essentially all horizons, as of June 19, declines in the employment-weighted average forecasts are usually about 50% larger relative to the market cap-weighted averages. For instance, the 2022 calendar revenue decline is 7.2% in the former versus 4.6% in the latter case, respectively. With the exception of 2020Q4, these differences are statistically significant at the 95% level. In brief, the stock market disproportionately captures news about a set of industries which are less exposed to the impact of the pandemic recession relative to the broader economy.

5 Assessing the Fiscal Response to Covid-19

As state and local governments began to impose widespread lockdowns and social distancing measures, policymakers were quick to respond with fiscal policies intended to limit the damage from the pandemic. While a formal treatment of optimal fiscal transfers is beyond the scope of this paper (see, e.g., Flynn, Patterson, and Sturm, 2020, and references therein for a more formal treatment), economic intuition suggests that an optimal insurance policy would provide the highest amount of relief to the hardest hit businesses—that is, the businesses most likely to cut investment, reduce employment, or shut down operations without receiving aid. Here, we explore whether the relief policies implemented in the first half of 2020 appear consistent with this objective.

In March 2020, the U.S. Congress passed the Coronavirus Aid, Relief, and Economic Security (CARES) Act, which included the Paycheck Protection Program (PPP). The PPP is a $669 billion loan program run by the U.S. Small Business Administration (SBA) intended to help smaller firms during the crisis; this program is the largest component of the fiscal stimulus provided to firms in the US. In order to be eligible for PPP financing, firms had to meet a size threshold; according to SBA, any business that prior to the crisis had 500 or fewer US-based employees or met SBA's alternative revenue/employment-based size standards would be eligible to receive funds.[24] Approved loan amounts vary based on the applicant's average payroll costs with a $100,000 annualized cap per employee and $10 million in total per firm; most loan disbursements are capped at 2.5 times the firm's average monthly payrolls costs from 2019. SBA guarantees the loans but does not lend directly to firms; rather, firms apply for PPP loans from authorized lenders. Most importantly, SBA forgives the loan if the firm maintains its entire workforce for a minimum of eight weeks and the loan is only used for payroll, rent, mortgage interest, or utility expenses, thus PPP is effectively a fiscal transfer to firms.[25]

[24] In addition to firms, any self-employed person, sole proprietor, independent contractor, 501(c)(3) non-profit organization, 501(c)(19) veterans' organization, or tribal business is eligible. Restrictions on size were relaxed for some firms in the Accommodations and Food Services sector (NAICS sector 72). Some firms who had currently or recently defaulted on SBA loans were deemed ineligible.

[25] The government has recently taken steps to relax certain requirements of the PPP with the PPP Flexibility Act (PPPFA) passed in early June. Originally, businesses had to spend at least 75% of the loan on payroll alone, but the PPPFA lowered this threshold to 60%. Whereas before firms only had only eight weeks to spend the entirety of the loan, the PPPFA extended the deadline to the end of 2020, giving firms the flexibility to wait and spend after they

First, we may expect that hardest-hit businesses are more likely to apply for PPP funding. Column (6) of Table 6 and Panel F of Figure 10 show that this is indeed the case. The SBP Survey also asks firms whether the firm applied for a PPP loan. In particular, the survey asks respondents "Since March 13, 2020, has this business requested financial assistance from the following Federal Sources?" and we tabulate the fraction of responses which check the "Paycheck Protection Program" box. Indeed Column (6) of Table 6 shows that a one standard deviation increase in exposure leads to a 3.6 percentage point increase in the likelihood of application. This magnitude is significant but pales in comparison to the intercept: a firm with the average level of exposure has a 75 percent probability of applying for PPP funds.

In brief, the vast majority of firms applied for PPP funding. But were funds allocated to the most exposed sectors? To answer this question, we next examine the correlation between our exposure measure and the total disbursements from the PPP program through July 10, 2020.[26] We augment this information with information at the firm level released by the Small Business Administration, which gives a more detailed picture of how the money is allocated. For loans less than \$150,000, the SBA reports the exact dollar value of the loan, while for loans larger than \$150,000, they report a range of dollar values the loan must fall within. The data also includes a field called "jobs saved," which we assume that it corresponds to the number of employees listed on the loan application form.[27] We interpolated the loan values that are not perfectly observed by taking the arithmetic mean of the endpoints of the bin. We validate this strategy by comparing to published state level totals, and while this by itself is quite close, it is biased upward relative to the published summary statistics for state and industry level totals. To correct for that bias, we simply calculate the average percentage miss at the state level, and use that to correct the values of the loans that are not perfectly observed. After this correction, our values almost exactly correspond to published totals, as is clear from Figure A.1 in the Appendix, which suggests other aggregations are likely close to the true unobserved ones.

In Table 8, we report the dollar amount of PPP funding per employee, as well as relative to the total annual payroll dollar amount. Examining the table, we see that the sector that received the largest number of PPP loans—and the second-highest total amount of funding—was "Professional and Technical Services" with 638,220 loans totaling approximately \$66 billion, which amounts to \$12,400 per employee. However, this sector was one of those *least* exposed to the disruptions associated with the pandemic: according to our calculations, this sector has the highest fraction of workers who can work remotely. By contrast, more exposed sectors received significantly less funding from the PPP program; "Accommodation and Food Services" and "Arts, Entertainment, and

have reopened.

[26] The data is available here.

[27] This field is sometimes missing or zero, suggesting that some firms elected not to disclose their current employment levels on the initial loan applications. As the distributions of loan sizes are fairly similar between the groups which report employment totals and those who do not, we replace zero or missing employment totals with the average number of employees reported by firms in the same industry and loan size bin. Results are qualitatively similar if we instead keep these numbers at zero.

Recreation", two of the hardest-hit sectors, received just \$5,000 and \$5,400 per worker, respectively.

Overall, we see that the least affected sectors actually received more PPP funds than the most affected sectors. What explains this inefficient provision of insurance? We believe the reason is that the PPP program treated most firms satisfying some basic criteria identically. Since loans were forgivable, take up rates for PPP are extremely high and thus most variation in total lending across eligible firms is driven by caps on benefit amounts. Average earnings per worker are considerably higher in sectors where working remotely is feasible (see, e.g. Dingel and Neiman, 2020, and section 2.1 above). Since benefit amounts are tied to average payroll, sectors with more white-collar workers (and thus higher average compensation) received more aid per worker. In brief, tying the amount of aid to total payroll had the (likely unintended) consequence of directing a larger share of total spending per employee towards the least exposed sectors.

With this data in hand, we get a much more detailed picture: rather than only looking at major sectors, we can now look at how the fiscal response is distributed across different NAICS4 industries. As we report in Figure 17 and Table 9, industries that are better able to transition to remote work, and thus experience a smaller supply side disruption, recieved far more dollars per worker than industries who were completely disrupted. A one-standard deviation increase in the severity of the supply side shock is associated with a 17.4% decrease in loan value per employee. In dollars, this corresponds to a loss of nearly \$1,700 relative to an average loan value of \$9,700. Equally striking is that there is no significant difference in the level of aid given to critical and non-critical industries, but the loan values for non-critical industries (who were more disrupted) are actually more sensitive to the shock than critical industries: a one standard deviation increase in our measure is associated with an average decrease in loan value per employee of 13.2% critical industries and 19.4% for non-critical industries.

In interpreting these findings, an important consideration is that the first round of stimulus was put in place quickly and at a time with immense economic uncertainty. Accordingly, policymakers elected to go for a large and broad-based response, offering aid to essentially all small businesses with few restrictions. To mitigate the costs of the pandemic, a more targeted program may be desirable, consistent with the view in Guerrieri et al. (2020). Though proposing an optimal policy is outside the scope of this paper, precedents exist. For example, the Department of Labor's Trade Adjustment Assistance program targets assistance to workers and firms displaced by foreign import competition (see, e.g., Hyman, 2018, for more details). Providing targeted assistance to workers and firms based on an ex-ante measure of exposure to Covid-19 work disruptions could be a more cost-effective way to alleviate the economic impacts of the virus.

6 Conclusion

We characterize the supply-side disruptions associated with Covid-19 by exploiting differences in the ability of workers across industries to work remotely. Our results uncover economically sizable differences in economic outcomes for both workers and firms depending on the ability of their industry to work remotely. Sectors in which a higher fraction of the workforce is not able to work remotely experienced significantly greater declines in employment, significantly more reductions in expected revenue growth, worse stock market performance, and higher expected likelihood of default. Lower-paid workers, especially female workers with young children, were significantly more affected by these disruptions.

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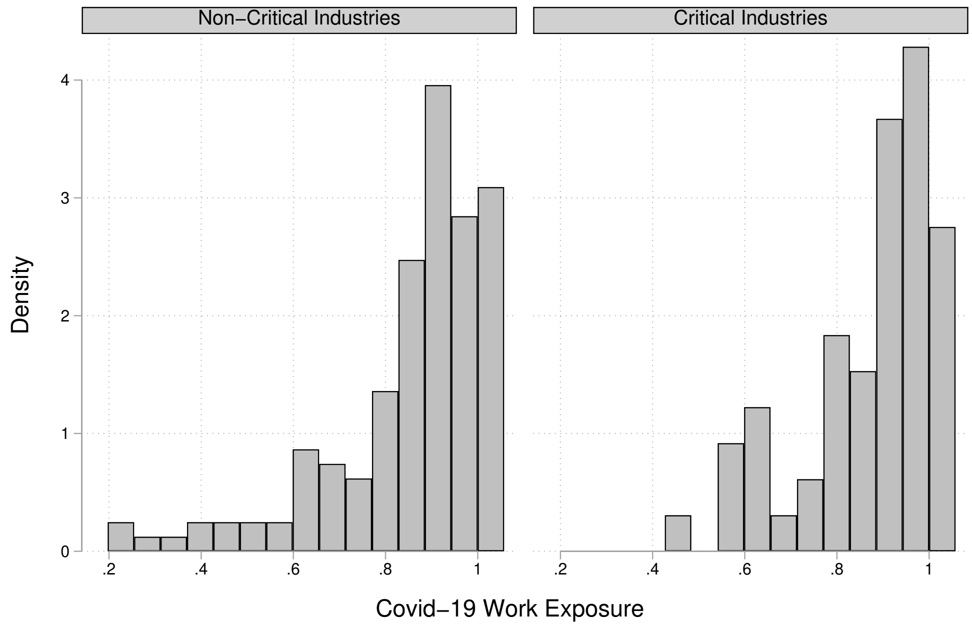
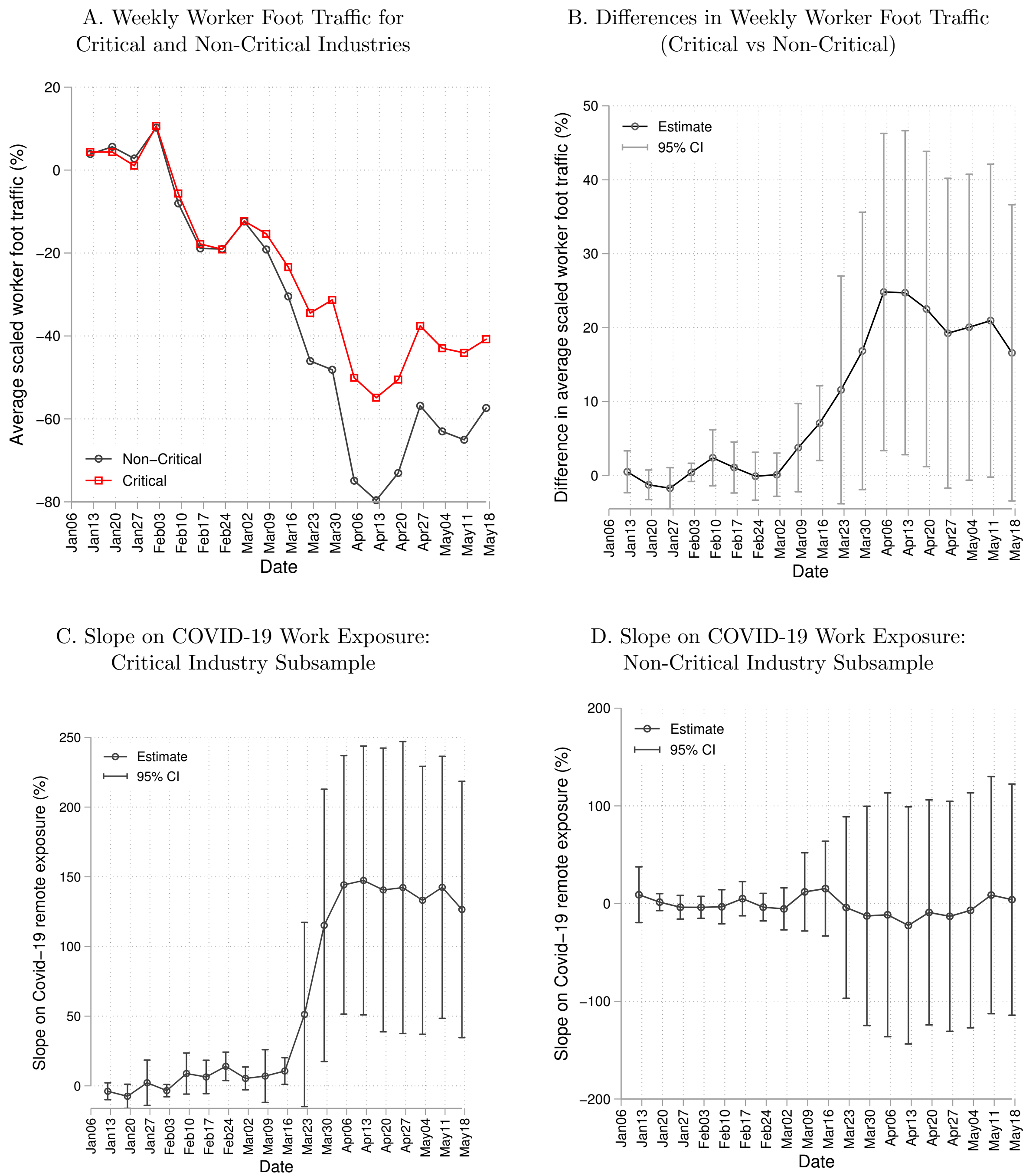
Figures and Tables

Figure 1: Distribution of Covid-19 Work Exposure Measure across Industries



The figure plots the distribution of the Covid-19 work exposure measure across critical (right panel) and non-critical (left panel) industries.

Figure 2: Changes in Worker Foot Traffic: Critical and Non-Critical Industries



The figure documents the differential decline in average worker foot traffic between critical and non-critical industries—given our classification in Appendix Table A.1. Panel A plots the average change in weekly worker foot traffic—$\log\left(\frac{\text{Total Worker Foot Traffic in week t in Industry I}}{\text{Pre-period Average Worker Foot Traffic of Industry I}}\right)$. Panel B plots the estimated β_t coefficients from equation (2) in the main document, which capture the differences in weekly foot traffic (relative to pre-period averages) between critical and non-critical industries. Panels C and D report δ_t coefficients from cross-sectional regressions of industry-level changes in worker foot traffic on our Covid-19 Work Exposure (equation (3)) measure for critical and non-critical industries, respectively. All regressions are weighted by total NAICS4 employment, and pre-period averages are computed from January 6-February 16 of 2020. Dates on the horizontal axis correspond with the end of each calendar week.

Figure 3: Employment Growth and Covid-19 work exposure

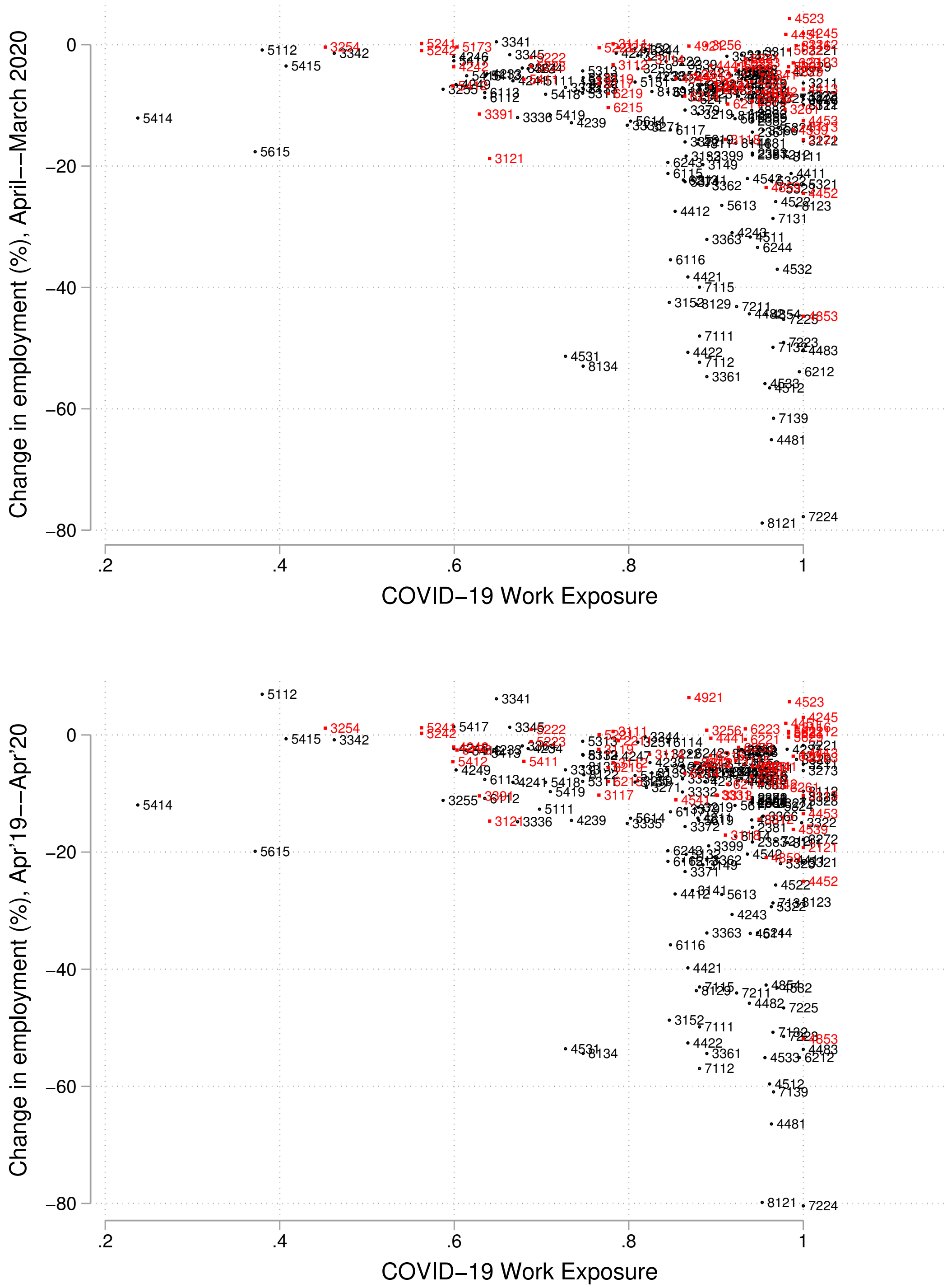
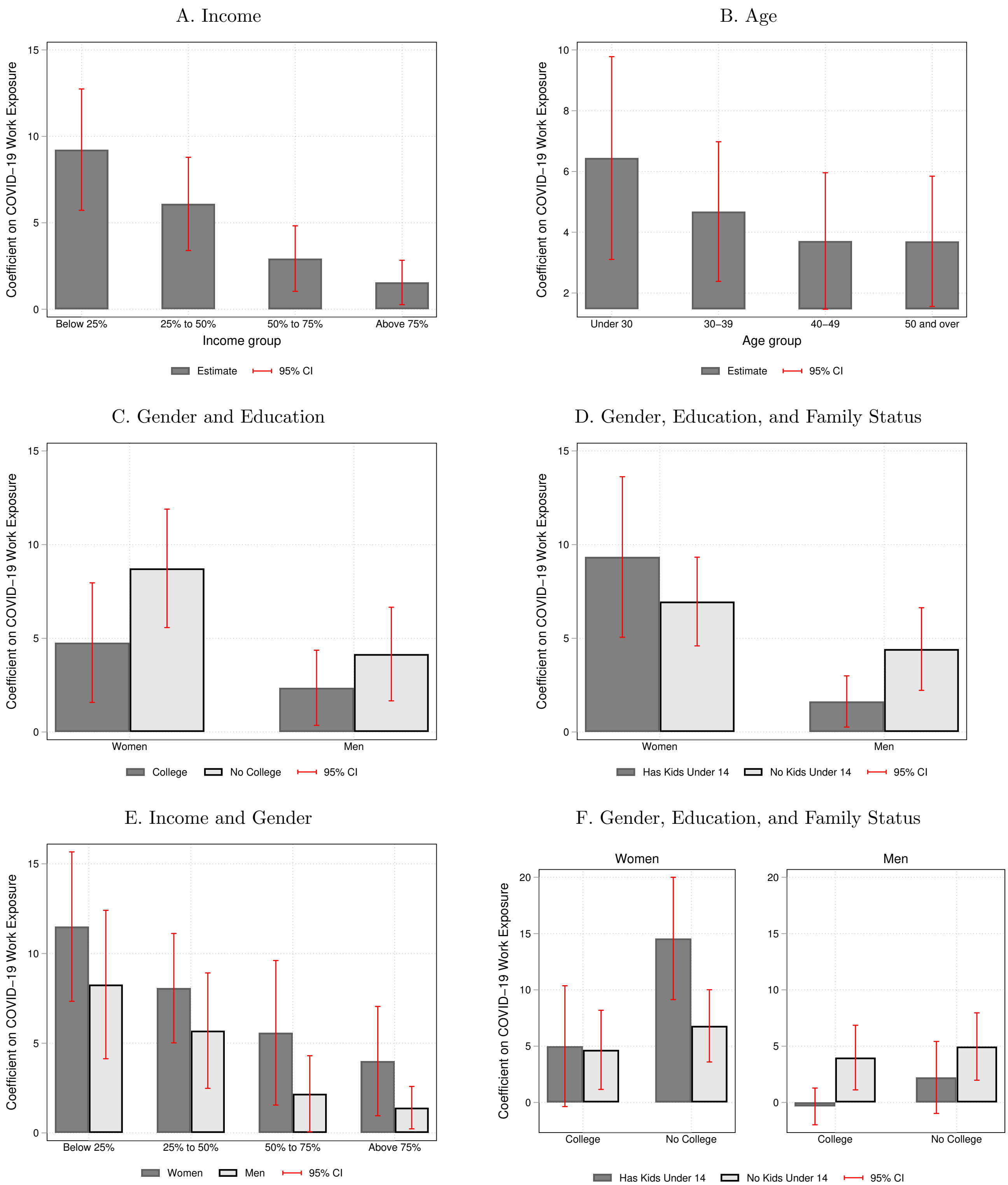


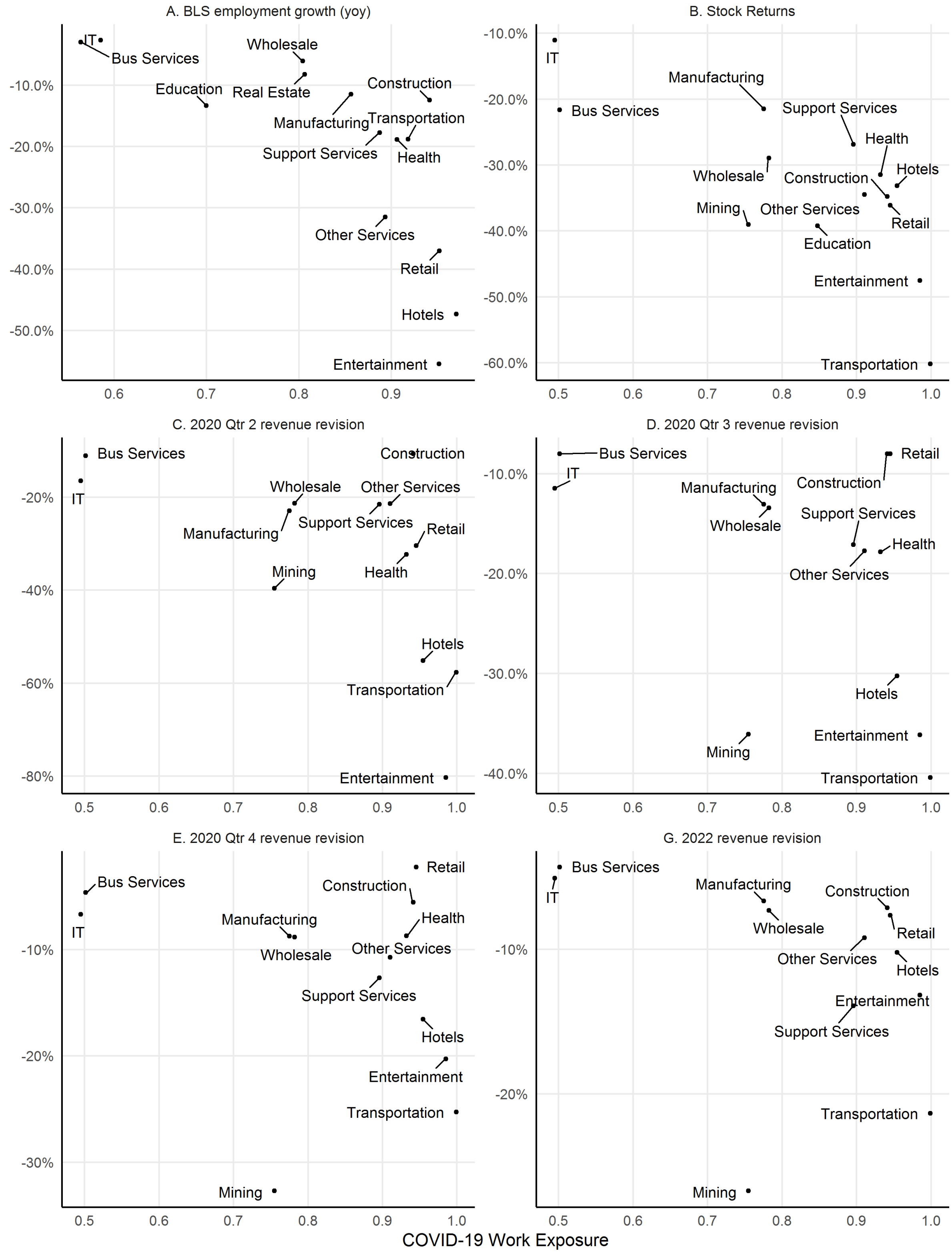
Figure plots the correlation between employment growth and Covid-19 work exposure at the 3-digit NAICS level. Top panel plots month-to-month changes (April vs March 2020) while the bottom plots year-on-year changes (April 2020 to April 2019). The points in red correspond to the critical industries listed in Appendix Table A.1.

Figure 5: Employment and Covid-19 work exposure: Worker Heterogeneity



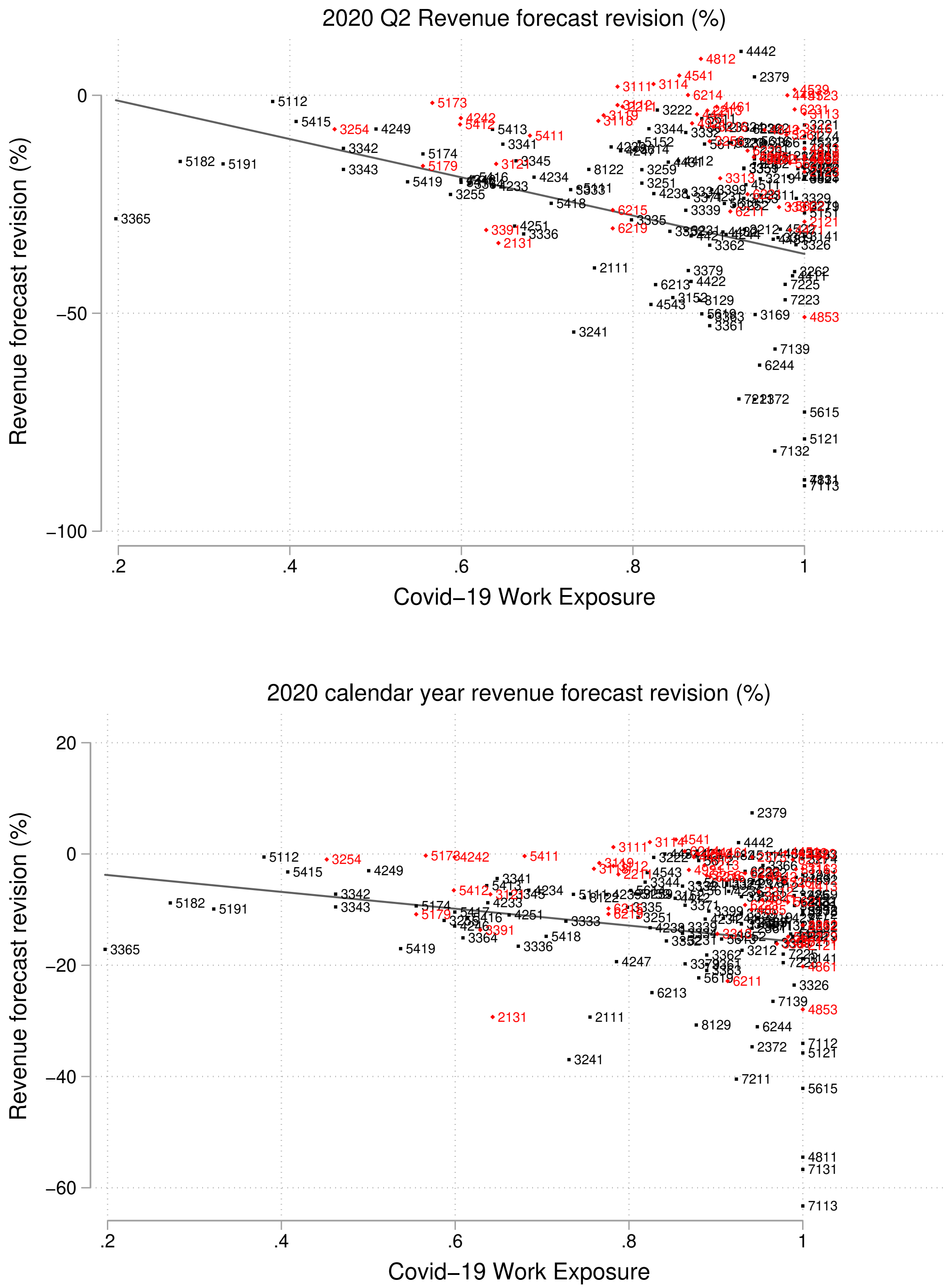
Figures plot how the coefficients of a regression of non-employment status on our Covid-19 work exposure measure vary with workers characteristics.

Figure 4: Real activity of non-critical industries and Covid-19 work exposure by major sector



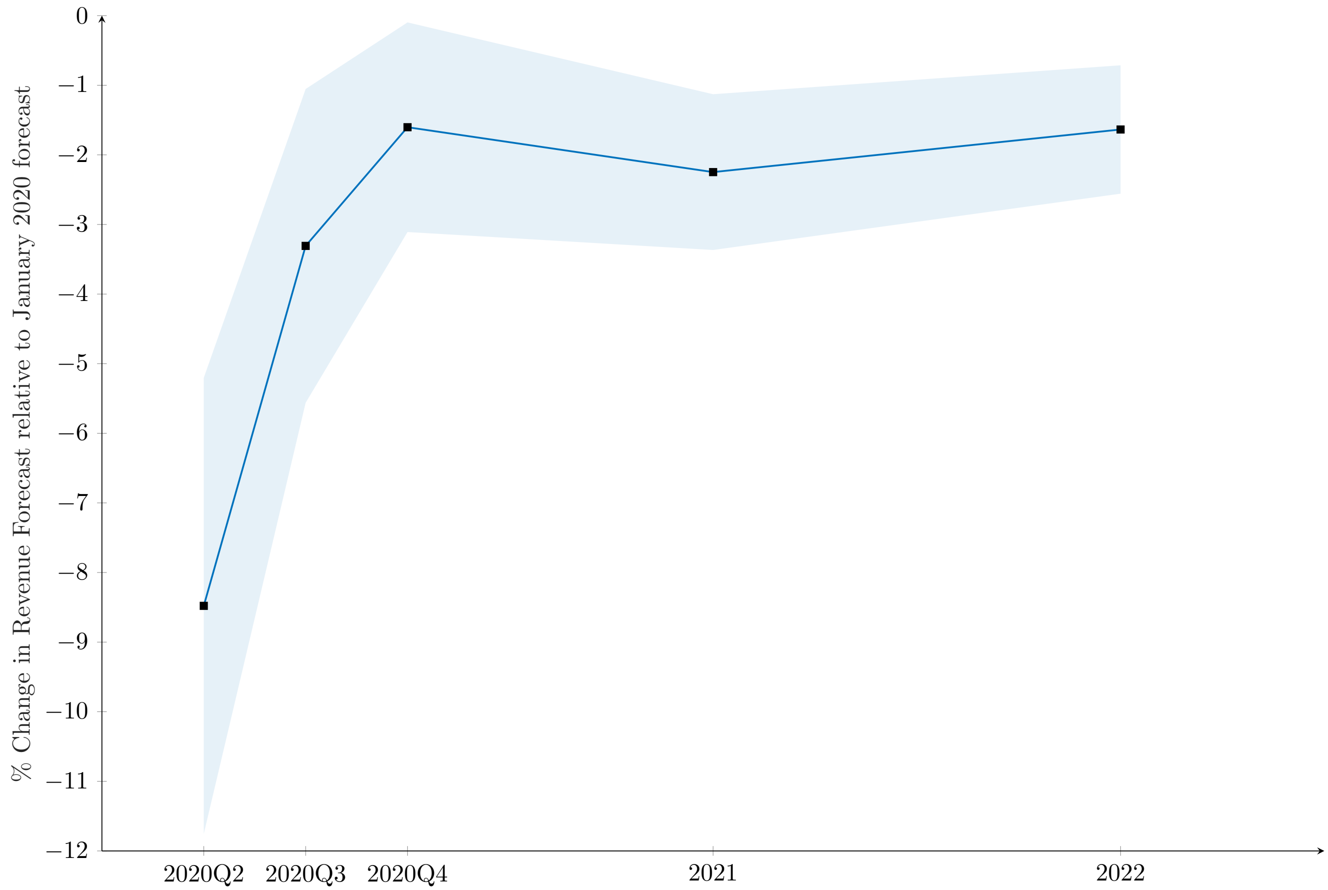
Panel A plots employment growth rates from April 2020 vs 2019 from the BLS against exposure (aggregated across 3-digit industries using BLS total employment weights). Panels B-F plot stock returns and revisions in revenue forecasts for non-critical industries from mid-February to mid-May versus the Covid-19 work exposure measure. For purposes of generating the graph, we average across 4-digit non-critical industries, weighting by Compustat employment.

Figure 6: Revenue forecast revisions and Covid-19 work exposure



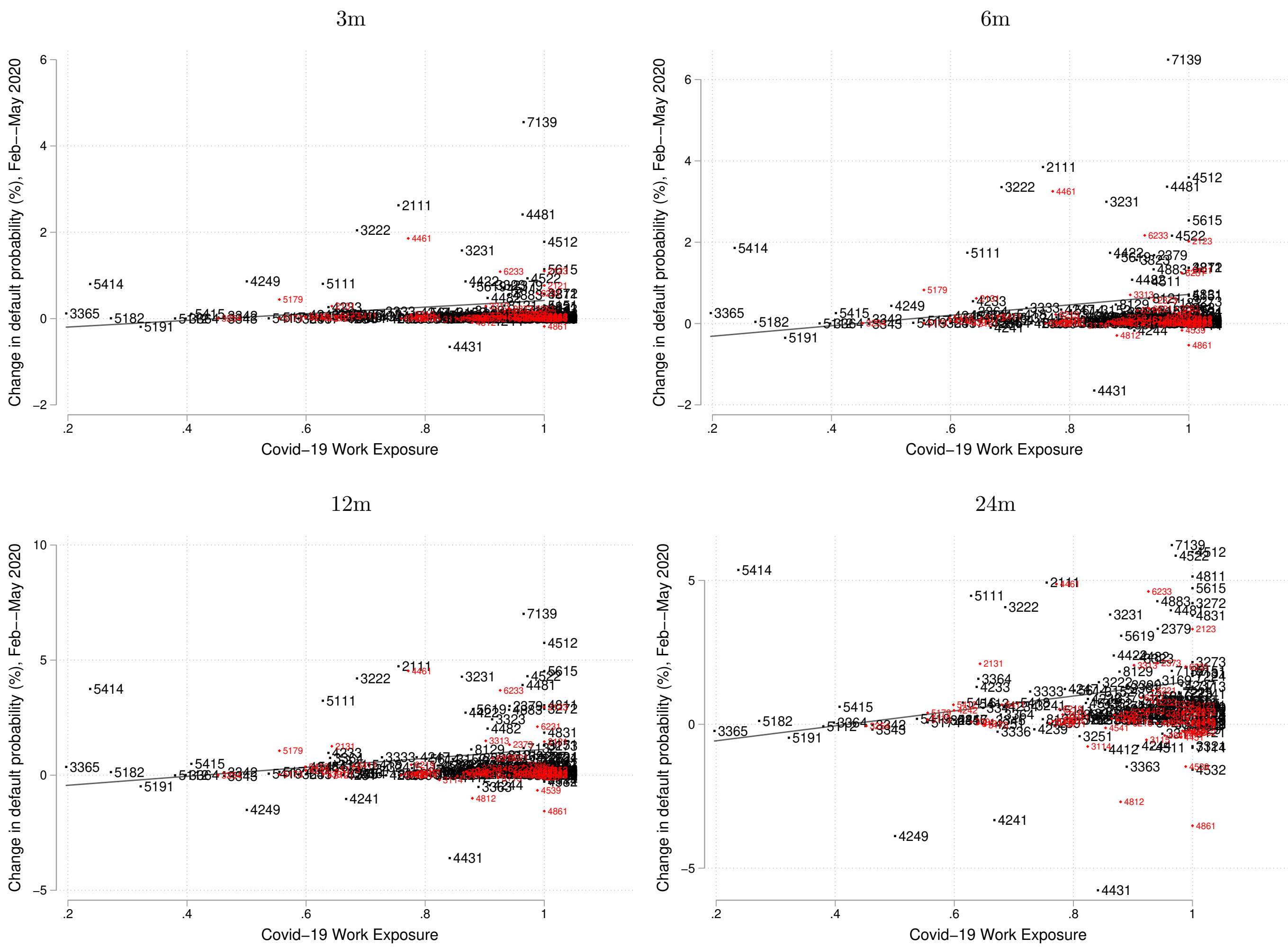
The top panel of this figure plots the revisions in revenue forecasts for Q2 2020 between mid-February and mid-May 2020 versus the Covid-19 work exposure measure. The bottom panel plots the corresponding revisions for the year 2020. The points in red correspond to the critical industries listed in Appendix Table A.1.

Figure 7: Revenue forecast revisions relative to February 2020 forecast as a function of Covid-19 work exposure



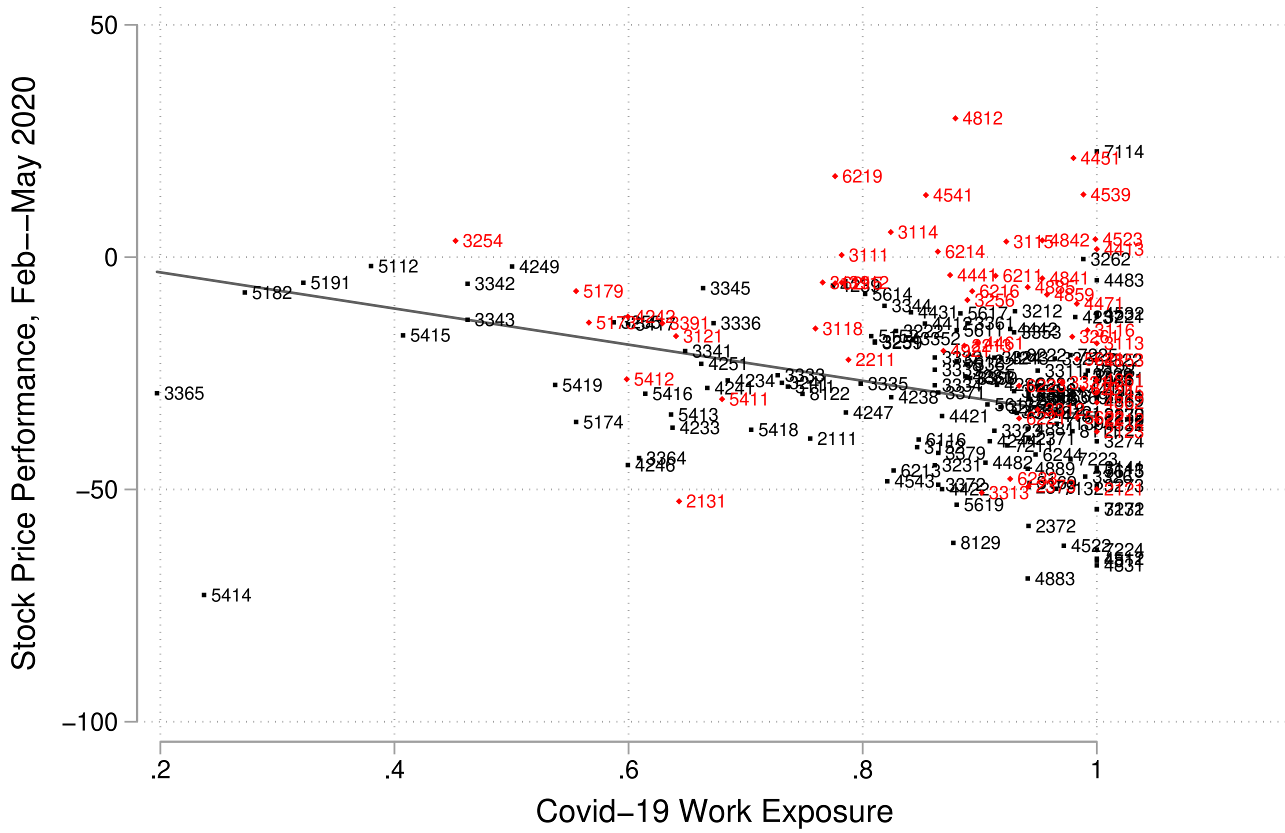
The Figure plots the estimated coefficients from equation (7) in the main document. Specifically, we plot the relation between revisions in industry-level revenue forecasts (from mid-February to mid-May 2020) as a function of their Covid-19 work exposure in the sub-sample of non-critical industries. The plotted coefficients correspond to columns (2)-(4) and (6)-(7) of Panel B of Table 4. Coefficients are standardized to a unit standard deviation change in the Covid-19 work exposure measure. Shaded areas correspond to 95% confidence intervals.

Figure 8: Default Probabilities and Covid-19 work exposure



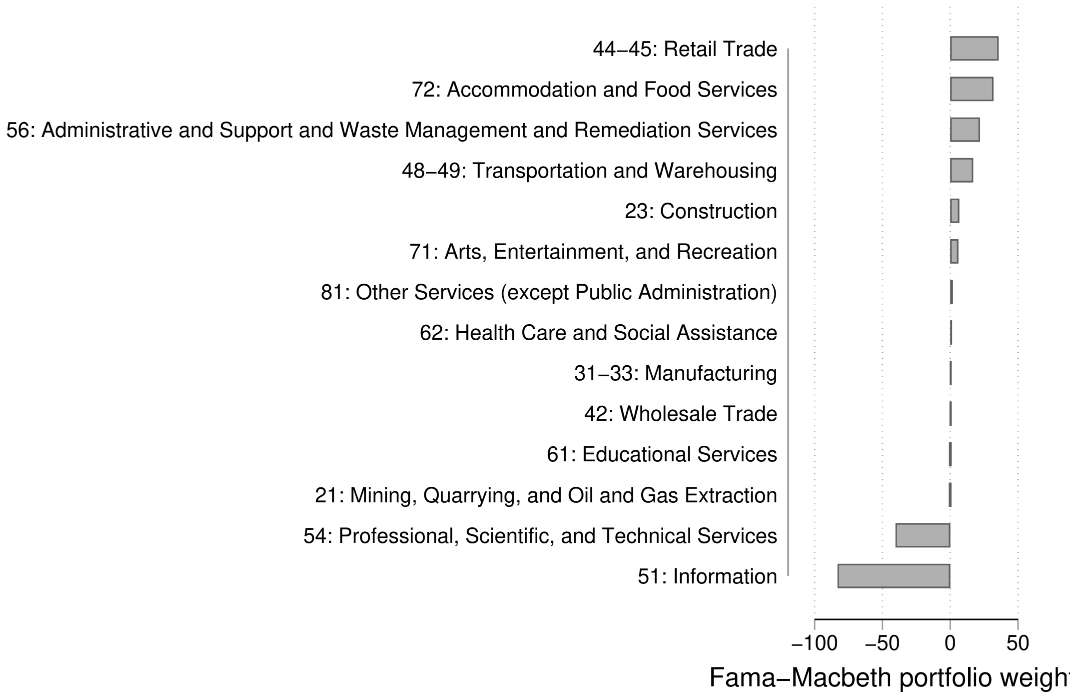
Panels of this figure plot changes in 3, 6, 12, and 24 month default probabilities for Q2 2020 between mid-February and mid-May 2020, respectively, versus the Covid-19 work exposure measure. The points in red correspond to the critical industries listed in Appendix Table A.1.

Figure 9: Stock Price change and Covid-19 work exposure



The figure plots the share price performance of different industries between mid-February to mid-May 2020 versus the Covid-19 work exposure measure. The points in red correspond to the critical industries listed in Appendix Table A.1.

Figure 11: COVID-19 factor: portfolio composition (NAICS 2-digit Industry)



This figure shows the loadings of our 'Covid-19 return factor' on broad industry sectors (defined at the 2-digit NAICS level). See Appendix Table A.2 for portfolio weights at a more detailed industry classification.

Figure 10: Covid-19 Work Exposure and Small Business Survey Responses: Binned scatter plots

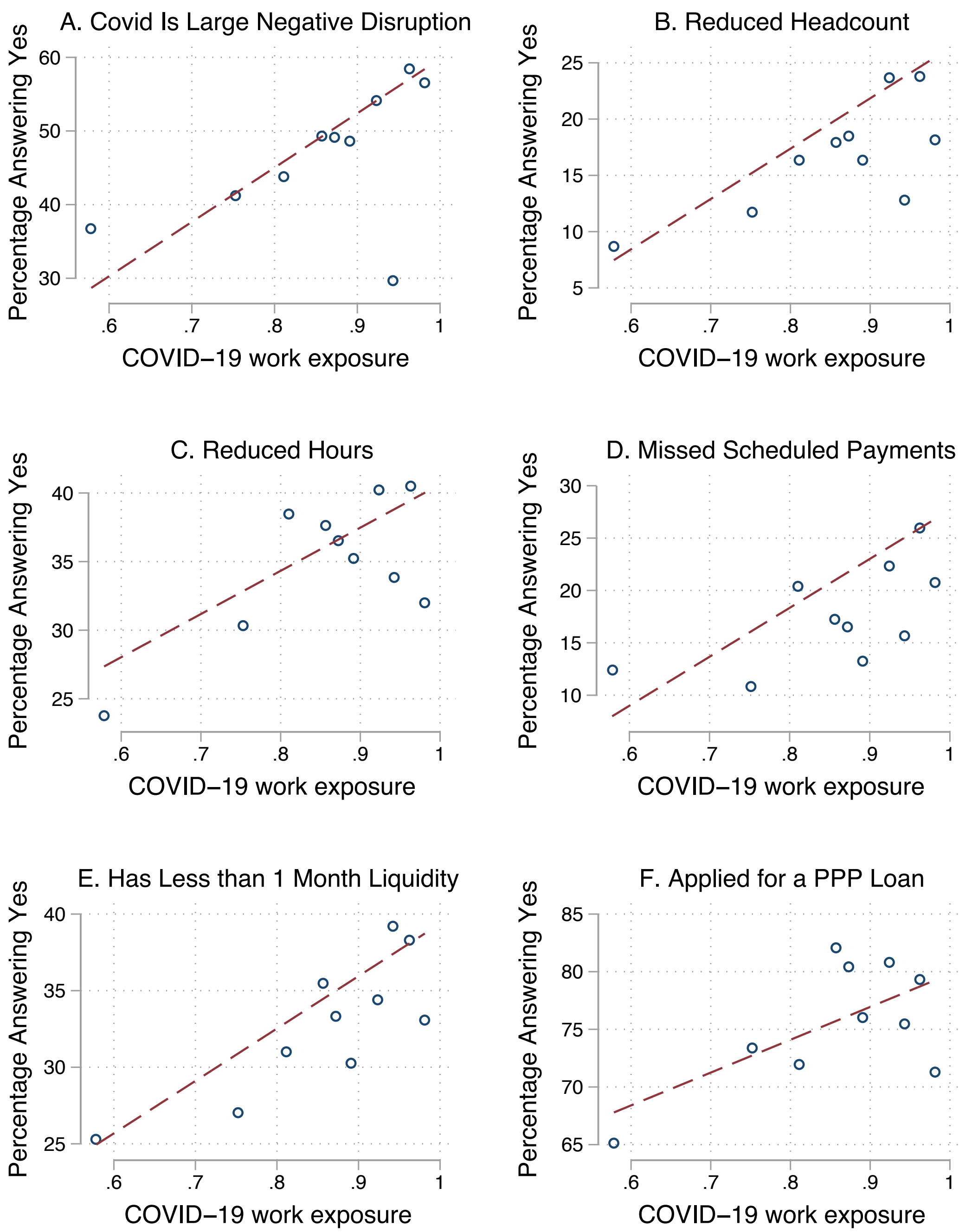
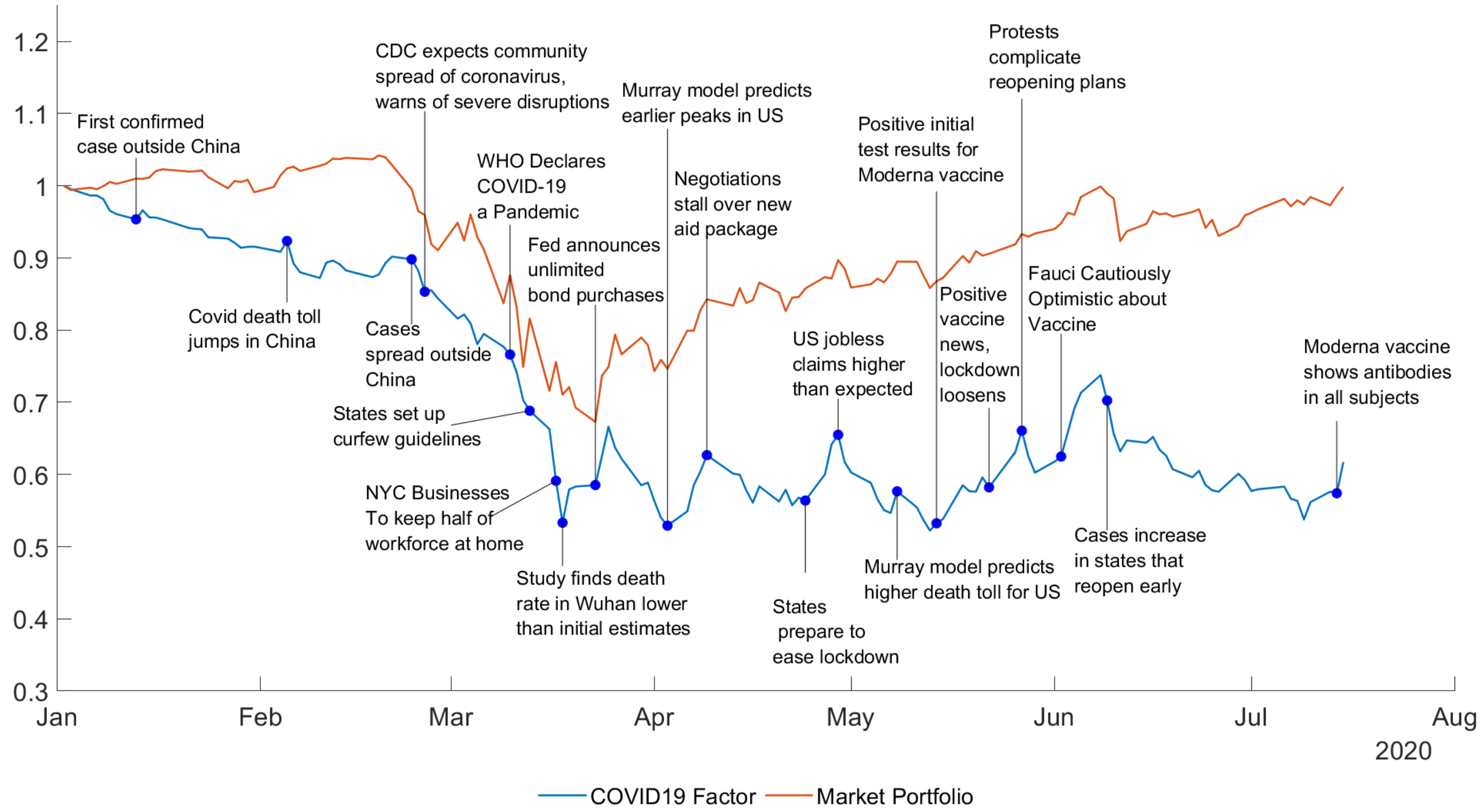


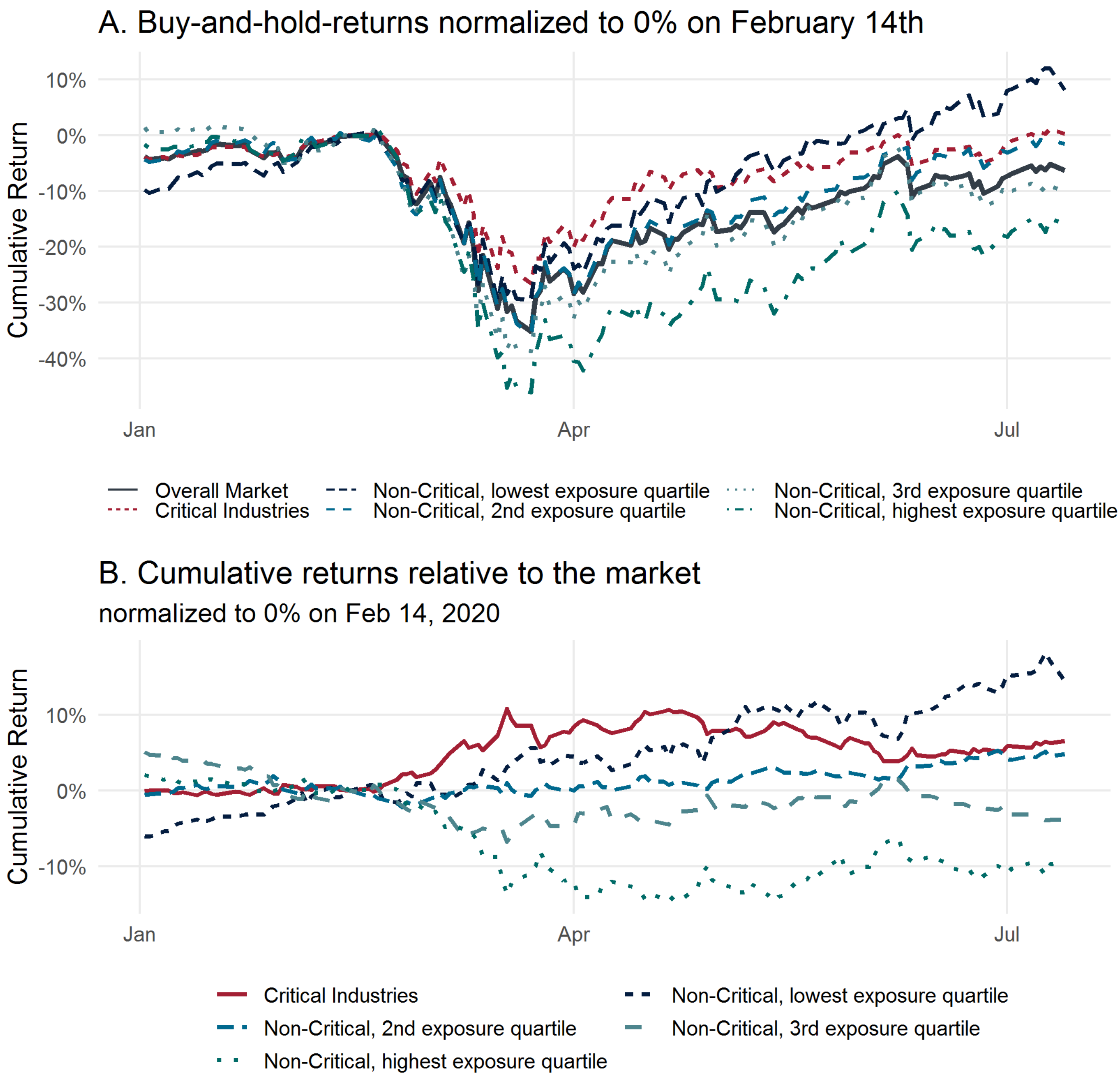
Figure reports binned scatter plots with the fraction of survey respondents who answered "Yes" to the six different questions from the first 6 waves of the Census' Small Business Pulse Survey, which are available at the 3-digit NAICS level, against our exposure measure for non-critical industries. 3-digit NAICS industries are sorted into 10 bins based on exposure, where, to compute bins and means within each bin, observations weighted by 2017 employment obtained from the Census' SUSB release. Please see notes to Table 6 for precise definitions of how we code each survey response.

Figure 12: COVID-19 factor vs market



The figure shows the time-series of the estimated slope coefficients in equation (11) in blue. As noted by Fama and MacBeth (1973) the realizations of these slope coefficients have a portfolio interpretation, here labeled as the 'Covid-19 return factor'. These implied portfolio returns are accumulated since beginning of the year. The red line represents cumulative returns to the market portfolio during this period. Events are dated as if they occurred at the beginning of the trading day on the date of their announcement.

Figure 13: Buy and hold returns for market, critical, and non-critical exposure-sorted portfolios



Panel A of the figure shows the buy and hold returns since January 1, 2020 for portfolios which are sorted on critical/non-critical status, and, within non-critical industries, sorted on our Covid-19 work exposure measure. Panel B reports the difference between cumulative returns of each portfolio since February 14, 2020 and the cumulative return of the market portfolio over the same period. Portfolios are value-weighted and breakpoints are chosen so that the non-critical portfolios each have approximately the same market cap as of February 14, 2020.

Figure 14: Revenue forecast revisions and Covid-19 work exposure over time

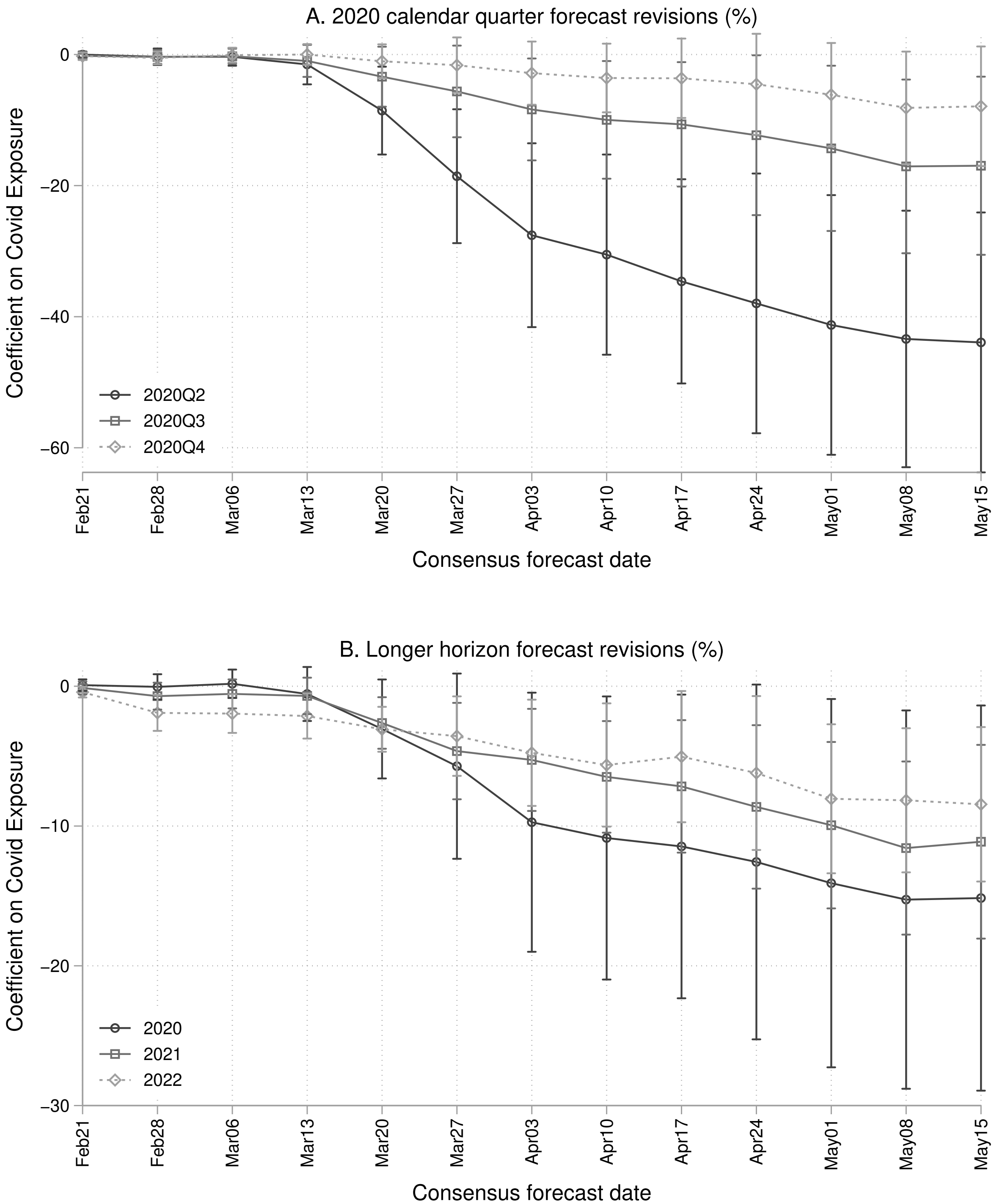


Figure plots the slope coefficients of a regression of forecast revisions on the (non-critical) industry's Covid-19 work exposure at a weekly frequency. The top panel of this figure plots the slope coefficient for revisions in revenue forecasts for Q2–Q4 2020. The bottom panel plots the corresponding revisions for the years 2020 through 2020.

Figure 15: Default Probabilities and Covid-19 work exposure over time

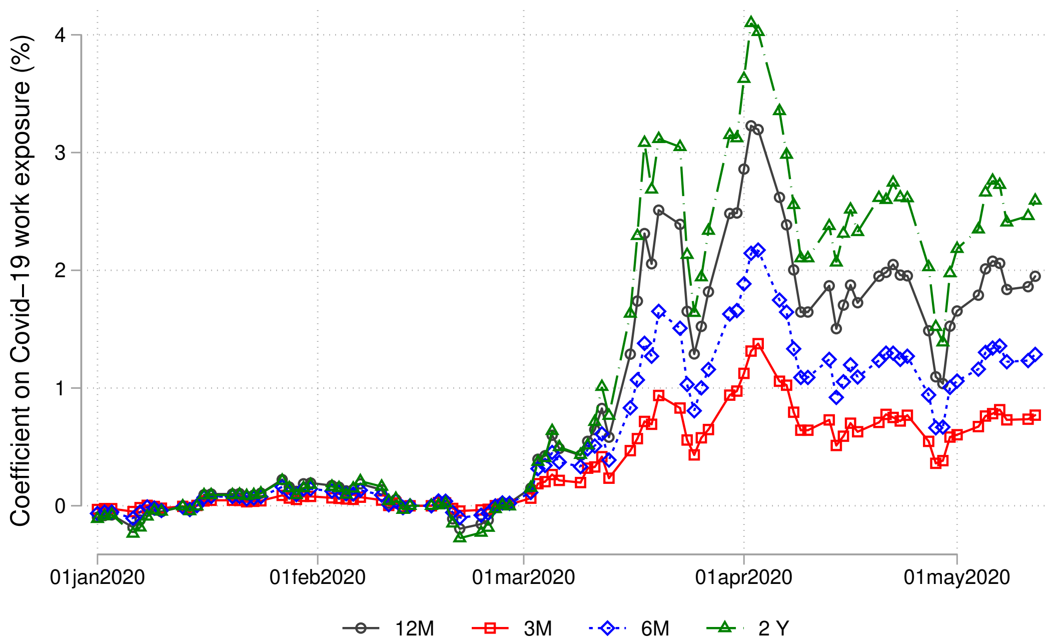


Figure plots the Fama-McBeth slope coefficients of a regression of default probabilities on the (non-critical) industry's Covid-19 work exposure at a daily frequency. The dependent variable is expressed in percentage points so that the slope coefficient can be interpreted as the increase, in basis points, of the probability of default associated with a 1 percentage point increase in exposure. Regressions are weighted by employment. Different colors correspond to different forecast horizons.

Figure 16: Stock returns and revenue forecast revisions: employment vs market cap weights

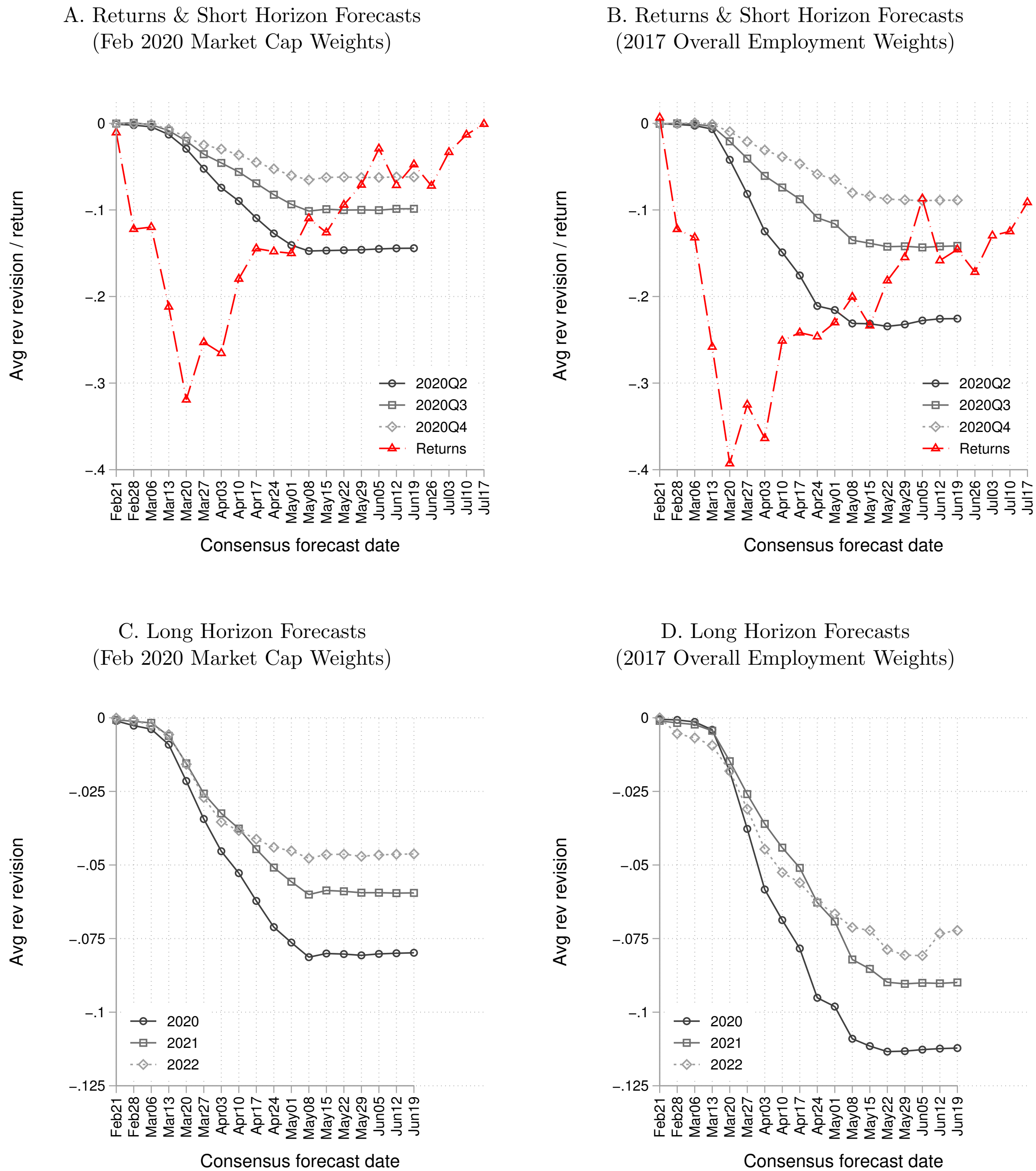
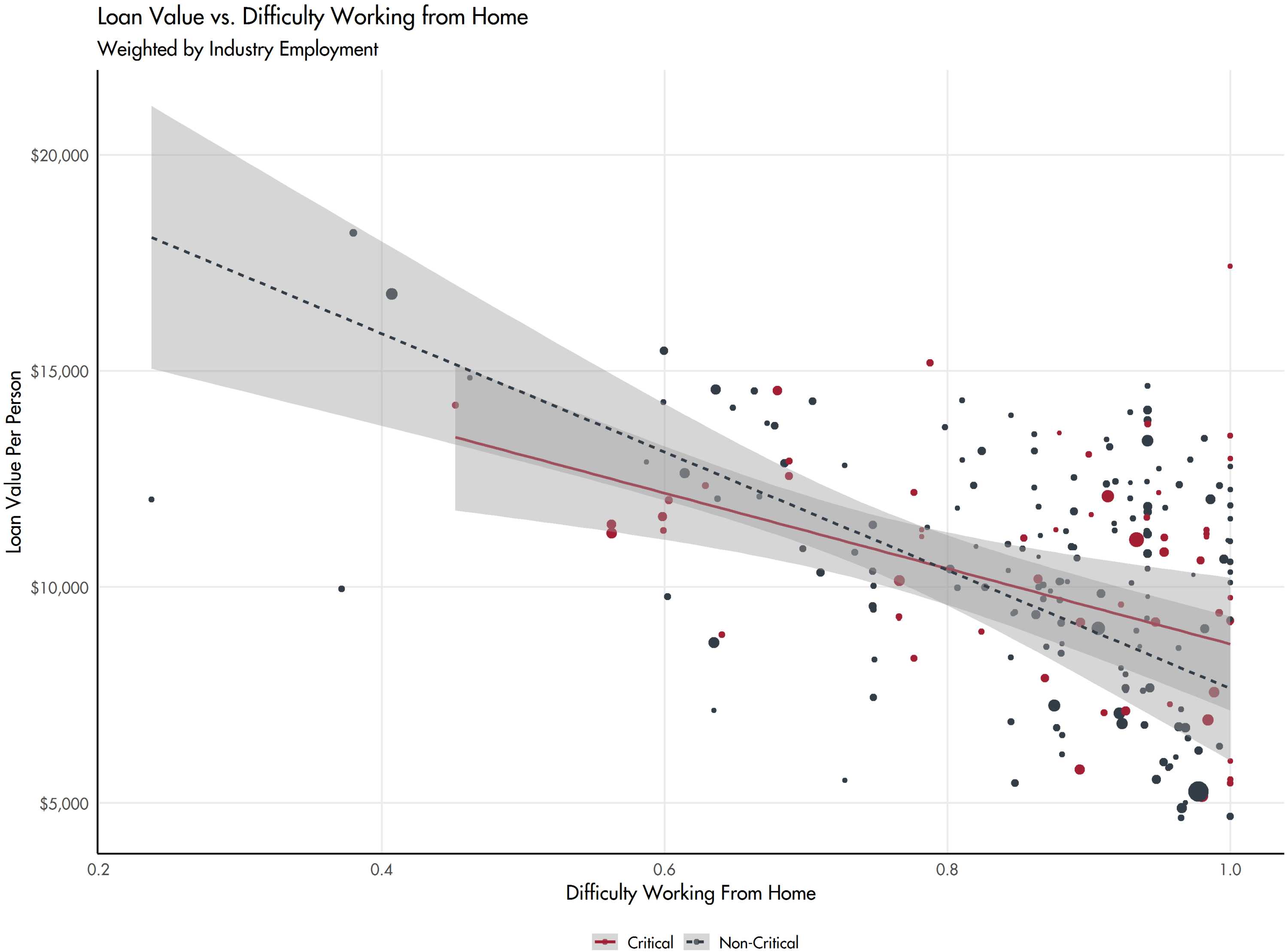


Figure plots average percentage forecast revisions at various horizons and cumulative stock returns from February 14 through various dates on a weekly basis. In the left panel, we weigh each four digit NAICS industry by the market cap of firms as of February 14, 2020. In the right panel, we weigh observations by total employment of publicly and privately held companies as of 2017. Panels A and B show stock returns and shorter horizon revenue forecast revisions, while panels C and D show longer horizon revenue forecasts. Dates on the horizontal axis correspond with the end of each calendar week.

Figure 17: Covid-19 Work Exposure and PPP Loan Value per Employee



This figure compares the loan value per employee, summed at the NAICS4 level, and grouped by the critical vs. non-critical designation. Loan values are based on microdata at the individual firm level provided by the Small Business Administration, using exact dollar values where available and otherwise interpolated by taking the midpoint of each loan size bin. These values are then aggregated at the NAICS4 industry level. Observations are weighted by industry employment obtained from the Census' SUSB data.

Table 1: Firm summary statistics by quartiles of Covid-19 work exposure

Firm characteristic (median)	A. All industries				B. Firms in non-critical industries			
	Covid work exposure bin:				Covid work exposure bin:			
	Lowest	2	3	Highest	Lowest	2	3	Highest
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Covid-19 work exposure	0.45	0.64	0.82	0.98	0.32	0.67	0.86	0.97
Sales ($ M)	41	471	1308	1479	414	769	1323	1360
Employment (thousands)	0.18	1.14	2.67	4.79	1.5	1	4.3	4.87
Market capitalization ($ M)	774	933	2059	1594	1914	1129	1599	1403
Tobin's Q	2.7	1.76	1.44	1.37	2.28	1.52	1.56	1.34
Book Debt to Book Assets (%)	40.2	52.7	57	61.1	53.3	52.9	55.5	62.3
R&D / Sales(%)	31.4	8.6	2.1	0.1	15.5	7.4	2.5	0.3
SG&A / Sales	60.9	32.5	19.7	15.5	49.4	23.5	20.6	16.3
PPE to Assets	12.2	25.2	52.9	62.1	16.4	32.5	36.1	58
Gross Profitability to Assets	11.9	29.7	23.8	23.3	34.7	24.1	29.6	23.1
Return on assets (ROA)	-19	7.8	10.6	11.2	6.1	9.3	10.8	11.4

Table reports median characteristics of firms in the Compustat database, grouped into quartiles based on our industry-based measure of Covid-19 work exposure. The left panel (A) summarizes these characteristics for all firms, including those in critical industries. The right panel (B) repeats the analysis for the subsample of firms which we classify as non-critical. The list of critical industries at the 4-digit NAICS level is in Appendix Table A.1. Gross profitability is sales (Compustat: sale) minus costs of goods sold (Compustat: cogs); Tobin's Q is computed as the sum of the book value of assets (Compustat: at) plus the market value of equity (Compustat: prcc_f times csho) minus the book value of equity (Compustat: ceq) minus deferred taxes (Compustat: txdb). PPE is Property Plant and Equipment (Compustat: ppegt).

Table 2: Covid-19 Work Exposure and Employment Growth

A. Month-on-month growth (%)	Weighted by Mar'20 employment		Equal weighted	
	All Industries	Non-Critical	All Industries	Non-Critical
	(1)	(2)	(3)	(4)
Covid-19 Work Exposure	-46.8***	-67.1***	-30.3***	-39.0***
	(-3.24)	(-4.47)	(-4.76)	(-4.61)
Number of observations	217	156	217	156
R^2	0.146	0.277	0.070	0.099
B. Year-on-year growth (%)	Weighted by April'19 employment		Equal weighted	
	All Industries	Non-Critical	All Industries	Non-Critical
	(5)	(6)	(7)	(8)
Covid-19 Work Exposure	-52.2***	-74.2***	-33.3***	-42.3***
	(-3.40)	(-4.71)	(-4.80)	(-4.62)
Number of observations	217	156	217	156
R^2	0.157	0.294	0.076	0.105
C. Average, all industries	Month-on-month growth		Year-on-year growth	
	Weighted	Unweighted	Weighted	Unweighted
	(9)	(10)	(11)	(12)
Critical Industries	-4.08***	-6.49***	-2.86***	-5.85***
	(-4.65)	(-6.65)	(-3.29)	(-5.20)
Non-Critical Industries	-22.47***	-17.54***	-22.60***	-17.73***
	(-6.09)	(-12.78)	(-5.69)	(-12.29)
Diff: Non-Critical-Critical	-18.39***	-11.06***	-19.75***	-11.88***
	(-4.85)	(-6.57)	(-4.86)	(-6.50)
Number of observations	217	217	217	217

Panels A and B of table reports the coefficients estimates from equation (4) in the document using employment-weighted and unweighted specifications (t-statistics in parantheses). Odd-numbered columns repeat the analysis for the subsample of non-critical industries. The dependent variable is expressed in percentage points and constructed using private sector employment data from the BLS' April 2020 employment report at the 4-digit NAICS level. Standard errors are robust to heteroskedasticity (White, 1980). The list of critical industries at the 4-digit NAICS level is in Appendix Table A.1. Panel C reports the average declines in the dependent variable for critical and non-critical industries, respectively, as well as the difference between the two averages. The cross-sectional standard deviation across BLS industries of the COVID factor exposure is 13.86%. Given that BLS only reports data for a single 4 digit agricultural industry (logging), we exclude agriculture from this analysis, though the results are not sensitive to this choice.

Table 3: Covid-19 Work Exposure and Worker Employment Outcomes

Probability (%) worker is not employed as of...	April 2020			February 2020
(conditional on being employed as of March 2020)	(1)	(2)	(3)	(4)
Critical industry	-9.2***	-9.2***	-8.1***	-0.2
	(-4.87)	(-5.32)	(-5.01)	(-0.63)
Non-critical industry × Covid-19 work exposure	50.6***	40.8***	36.0***	-0.9
	(6.28)	(5.24)	(4.77)	(-0.59)
Critical industry × Covid-19 work exposure	28.4***	18.1**	10.8	-4.1
	(3.22)	(2.11)	(1.43)	(-1.56)
Controls				
College Graduate Dummy		-6.3***	-3.8***	-0.4
		(-5.34)	(-3.27)	(-0.88)
Female Dummy		4.6***	3.2**	1.5***
		(3.14)	(2.16)	(2.83)
Kids under 14		-2.3*	-1.7	-0.1
		(-1.65)	(-1.30)	(-0.08)
Female Dummy × Kids under 14		4.0**	2.8	-0.4
		(2.24)	(1.58)	(-0.56)
College Graduate Dummy × Kids under 14		-0.1	0.6	-0.7
		(-0.09)	(0.45)	(-0.94)
Age 30 to 39		-2.5*	-0.7	-0.5
		(-1.79)	(-0.56)	(-0.50)
Age 40 to 49		-3.4***	-1.2	-0.5
		(-2.79)	(-0.90)	(-0.56)
Age 50+		-2.7**	-0.2	-0.7
		(-2.23)	(-0.19)	(-0.82)
2019 earnings in bottom quartile			12.5***	1.8***
			(6.88)	(3.53)
2019 earnings in 2nd quartile			6.2***	0.5
			(4.76)	(1.20)
2019 earnings in 3rd quartile			2.0***	0.1
			(2.87)	(0.49)
Firm size: Under 10			2.4	0.5
			(1.27)	(0.71)
Firm size: 10 to 99			1.0	-0.3
			(0.58)	(-0.63)
Firm size: 100 to 999			-0.8	0.1
			(-0.74)	(0.23)
Constant	0.179***	0.205***	0.121***	0.0135
	(10.19)	(10.09)	(6.20)	(1.53)
Number of observations	9,660	9,273	9,273	6,193
R^2	0.040	0.056	0.075	0.010

Table reports the coefficients estimates from equation (9) in the document. Standard errors are double-clustered based on occupation and industry (t-statistics in parantheses). The dependent variable is an indicator which equals one if an individual does not have a job in April (columns 1-3) or February (column 4) 2020. To be included in the sample, workers need to appear in the March 2020 CPS and March 2019 ASEC survey, and either the April and/or February core CPS sample. The list of critical industries at the 4 digit NAICS level is in Appendix Table A.1. We define critical Census industries as those for which at least 50% of employment is associated with critical NAICS industries. The cross-sectional standard deviation of the exposure measure for workers in our sample is 12.4%.

Table 4: Covid-19 Work Exposure, Stock Returns and Analyst Forecasts

A. Regressions for Non-Critical Industries	Stock Returns (%)	Analyst Forecast Revisions (%) 2020Q2	2020Q3	2020Q4	2020	2021	2022
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Covid-19 Work Exposure	-38.9***	-43.9***	-17.1**	-8.3*	-15.1**	-11.6***	-8.5***
	(-5.37)	(-4.32)	(-2.45)	(-1.78)	(-2.13)	(-3.35)	(-2.96)
Observations	141	126	127	127	127	127	92
R^2	0.295	0.229	0.099	0.053	0.077	0.151	0.134
B. Averages, All Industries							
Critical industries	-8.0**	-6.8***	-4.5***	-2.7**	-3.2***	-2.5**	-2.3**
	(-2.02)	(-3.08)	(-3.17)	(-2.54)	(-2.71)	(-2.15)	(-2.49)
Non-critical industries	-25.6***	-26.5***	-15.3***	-9.4***	-12.5***	-9.9***	-7.9***
	(-10.53)	(-8.67)	(-8.58)	(-7.90)	(-6.82)	(-10.08)	(-9.57)
Diff: Non-critical - Critical	-17.6***	-19.7***	-10.7***	-6.7***	-9.2***	-7.4***	-5.6***
	(-3.78)	(-5.24)	(-4.69)	(-4.22)	(-4.23)	(-4.84)	(-4.52)
Number of observations	203	181	182	182	184	183	140

Table, panel A, plots the coefficients estimates from equations (10) and (7) in the document for non-critical industries, where the dependent variables are constructed using firm data from Compustat and Capital IQ, aggregated to the 4-digit NAICS level. The regression is weighted by total Compustat 2019 employment in each industry. Standard errors are robust to heteroskedasticity (White, 1980). Panel B reports averages of each outcome for critical and non-critical industries, as well as differences between the two. The list of critical industries is in Appendix Table A.1. The cross-sectional standard deviation of exposure across critical industries is 17.4%

Table 5: Covid-19 Work Exposure and Default Probabilities

A. Regressions for Non-Critical Industries	Change in probability of default (%) in next			
	3 months (1)	6 months (2)	12 months (3)	24 months (4)
Covid-19 Work Exposure	0.77*	1.27**	1.91***	2.52***
	(1.81)	(2.15)	(2.62)	(3.05)
Observations	155	155	155	155
R^2	0.071	0.086	0.102	0.111
B. Averages, All Industries				
Critical Industries	0.103***	0.195***	0.306***	0.307**
	(2.96)	(3.03)	(3.04)	(2.50)
Non-Critical Industries	0.509***	0.858***	1.263***	1.483***
	(2.77)	(3.28)	(4.07)	(4.71)
Diff: Non-critical - Critical	0.405**	0.663**	0.957***	1.176***
	(2.17)	(2.46)	(2.94)	(3.48)
Observations	221	221	221	221

Table plots the coefficients estimates from equation (8) in the document for non-critical industries, where the dependent variables are constructed using firm data from Compustat and the RMI Credit Research Database, aggregated to the 4-digit NAICS level (t-statistics in parantheses). The dependent variable is expressed in percentage points so that the slope coefficient can be interpreted as the increase, in basis points, of the probability of default associated with a 1 percentage point increase in exposure. The regression is weighted by total Compustat 2019 employment in each industry. Standard errors are robust to heteroskedasticity (White, 1980). The list of critical industries is in Appendix Table A.1. Panel B reports average changes in default probabilities, in percentage points, for critical and non-critical industries, respectively, as well as differences between the two means.

Table 6: Covid-19 Work Exposure and Small Business Pulse Survey Responses

A. Regressions for All Industries	Major Disruption (1)	Reduced Headcount (2)	Reduced Hours (3)	Missed Payments (4)	< 1 Month Liquidity (5)	Applied PPP (6)
Covid-19 Work Exposure	65.87***	39.46***	28.13***	36.95**	30.86***	27.16***
	(3.52)	(4.20)	(3.24)	(2.22)	(4.59)	(2.85)
Constant	46.52***	18.77***	35.03***	18.35***	33.61***	74.46***
	(14.88)	(13.66)	(27.66)	(7.36)	(24.92)	(55.49)
Observations	80	80	80	80	80	80
R^2	0.219	0.377	0.203	0.163	0.239	0.158
B. Regressions for Non-Critical Industries	**Major Disruption (1)**	**Reduced Headcount (2)**	**Reduced Hours (3)**	**Missed Payments (4)**	**< 1 Month Liquidity (5)**	**Applied PPP (6)**
Covid-19 Work Exposure	73.77***	44.72***	31.48***	46.72**	34.21***	28.48***
	(3.21)	(3.63)	(3.25)	(2.31)	(7.14)	(3.12)
Constant	49.22***	19.91***	36.12***	20.99***	34.47***	75.71***
	(11.80)	(11.42)	(33.51)	(6.55)	(39.44)	(66.86)
Observations	54	54	54	54	54	54
R^2	0.279	0.453	0.378	0.259	0.526	0.365

Table reports coefficient estimates (and robust t-statistics in parentheses) from OLS regressions of the fraction of survey respondents who answered "Yes" to the six different questions from the first 6 waves of the Census' Small Business Pulse Survey, which are available at the 3-digit NAICS level. Regressions are weighted by 2017 employment obtained from the Census' SUSB release. We define yes responses based on the following survey questions and answers. Major Disruption: (Q) "Overall, how has business been affected by the COVID-19 pandemic?" (A) Large Negative Effect. Reduced Headcount: (Q) "In the last week, did this business have a change in the number of paid employees?" (A) Yes, decreased. Reduced Hours: (Q) "In the last week, did this business have a change in the total number of hours worked by paid employees?" (A) Yes, decreased. Missed Payments: (Q) "Since March 13, 2020, has this business missed any other scheduled payments, not including loans? Examples of other scheduled payments include rent, utilities, and payroll." (A) Yes. < 1 Month Liquidity: (Q) "How would you describe the current availability of cash on hand for this business, including any financial assistance or loans? Currently, cash on hand will cover:" (A) 1-7 days of business operations through 3–4 weeks of business operations. Applied PPP: "Since March 13, 2020, has this business requested financial assistance from the following Federal Sources?" (A) Paycheck Protection Program. The cross-sectional standard deviation of exposure across NAICS3 industries is 12.7%

Table 7: Aggregate Stock Returns and Analyst Revenue Forecast Revisions with Employment versus Market Cap Weights

		Stock	Analyst Revenue Forecast Revisions (%)				
Date	Statistic	Returns (%)	2020Q2	2020Q3	2020Q4	2021	2022
3/20	Employment-weighted mean	-0.393	-0.042	-0.021	-0.010	-0.015	-0.018
	Market cap-weighted mean	-0.319	-0.029	-0.020	-0.016	-0.015	-0.016
	Difference	-0.074	-0.013	0.000	0.006	0.001	-0.002
	t statistic	(-3.133)	(-0.913)	(-0.055)	(0.992)	(0.134)	(-0.367)
4/17	Employment-weighted mean	-0.242	-0.176	-0.088	-0.047	-0.051	-0.056
	Market cap-weighted mean	-0.145	-0.109	-0.069	-0.045	-0.045	-0.041
	Difference	-0.097	-0.066	-0.018	-0.002	-0.006	-0.015
	t statistic	(-4.027)	(-2.000)	(-1.054)	(-0.151)	(-0.671)	(-1.339)
5/15	Employment-weighted mean	-0.234	-0.231	-0.139	-0.084	-0.085	-0.072
	Market cap-weighted mean	-0.126	-0.147	-0.099	-0.062	-0.059	-0.046
	Difference	-0.108	-0.085	-0.039	-0.021	-0.027	-0.026
	t statistic	(-3.742)	(-2.626)	(-1.928)	(-1.400)	(-1.994)	(-2.291)
6/19	Employment-weighted mean	-0.146	-0.226	-0.142	-0.089	-0.090	-0.072
	Market cap-weighted mean	-0.047	-0.144	-0.099	-0.062	-0.059	-0.046
	Difference	-0.098	-0.081	-0.043	-0.027	-0.030	-0.026
	t statistic	(-3.614)	(-2.678)	(-2.133)	(-1.674)	(-2.022)	(-2.447)

Table provides estimates of overall aggregated stock market performance and percentage revisions in analysts' forecasts from February 14th, 2020 through various dates under two different weighting schemes. First, we weigh observations by total employment of publicly and privately held companies as of 2017. Then, we consider an alternative in which we weigh each four digit NAICS industry by the market cap of firms as of February 14, 2020. We then report the difference and a t-statistic on the difference between the two estimates, which is using a weighted regression with standard errors clustered at the 4-digit NAICS level. Using these same weighting schemes, average Covid-19 Work Exposure is 87% when weighting by employment and 66% when weighting by market cap, where the difference of 21% is associated with a t-statistic of 4.8.

Table 8: Covid-19 Remote Exposure and PPP Loan Disbursements by Major NAICS sector

Industry Category	Remote Exposure	# Loans	Total Amount ($B)	% of Total	Employees (Raw, M)	Employees (Interp., M)	PPP / Employee (Raw)	PPP / Employee (Interp)
Health Care and Social Assistance	90%	506,259	$66.8	13.16%	7.52	8.24	$8,884	$8,103
Professional, Scientific, and Technical Services	58%	638,220	$65.9	12.99%	4.85	5.32	$13,596	$12,399
Construction	94%	466,212	$64.1	12.63%	5.08	5.59	$12,618	$11,475
Manufacturing	84%	229,559	$53.7	10.58%	4.60	4.95	$11,668	$10,842
Accommodation and Food Services	97%	367,499	$41.9	8.25%	7.58	8.29	$5,522	$5,054
Retail Trade	94%	450,177	$40.1	7.90%	4.75	5.19	$8,430	$7,724
Other Services (except Public Administration)	86%	531,568	$30.9	6.08%	4.08	4.57	$7,576	$6,757
Wholesale Trade	81%	167,235	$27.5	5.42%	2.35	2.54	$11,700	$10,844
Administrative and Support and Waste Management and Remediation Services	87%	240,932	$26.2	5.16%	3.04	3.39	$8,610	$7,727
Transportation and Warehousing	96%	191,608	$16.9	3.33%	1.69	1.88	$10,016	$9,013
Real Estate and Rental and Leasing	89%	245,696	$15.4	3.04%	1.46	1.62	$10,562	$9,541
Finance and Insurance	68%	168,460	$12.0	2.36%	1.00	1.10	$12,024	$10,912
Educational Services	80%	81,387	$11.9	2.34%	1.43	1.58	$8,296	$7,511
Information	62%	69,103	$9.2	1.81%	0.71	0.77	$12,991	$11,907
Arts, Entertainment, and Recreation	91%	118,331	$8.0	1.57%	1.34	1.48	$5,957	$5,369
Agriculture, Forestry, Fishing & Hunting	93%	139,146	$7.9	1.55%	1.05	1.16	$7,475	$6,811
Mining, Quarrying, and Oil & Gas Extraction	88%	21,568	$4.5	0.88%	0.29	0.31	$15,284	$14,412
Management of Companies and Enterprises	69%	8,893	$1.6	0.31%	0.15	0.16	$10,514	$9,783
Utilities	89%	7,928	$1.5	0.29%	0.11	0.11	$14,015	$12,968
Public Administration	NA	13,423	$1.7	0.34%	0.16	0.17	$10,811	$9,942

Table reports summary statistics on Paycheck Protection Program loan disbursements by major NAICS sector, along with employment and payroll information for the set of firms participating in the program is taken from the published data at the individual loan data. Payroll data is taken from microdata released by the SBA, which reports number of "jobs saved" associated with each job. The first employment figure "Emp. (Raw, M)" is a raw total of this value by sector, while the latter total "Emp. (Interp, M)" imputes zero/missing values with industry $\times$ loan size bin averages. The final two columns express total loan disbursements on a per-employee basis by dividing total loan disbursements by each of these total employment figures.

Table 9: Covid-19 Work Exposure and Loan Value ($) per Employee

A. $/Employee	Weighted by employment		Equal weighted	
	All Industries (1)	Non-Critical (2)	All Industries (3)	Non-Critical (4)
Covid-19 Work Exposure	-12116.6***	-13691.8***	-7017.4***	-7474.9***
	(-5.56)	(-5.09)	(-5.28)	(-4.37)
Number of observations	217	156	217	156
R^2	0.327	0.368	0.134	0.145
B. log($/Employee)*100	Weighted by employment		Equal weighted	
	All Industries (5)	Non-Critical (6)	All Industries (7)	Non-Critical (8)
Covid-19 Work Exposure	-125.9***	-139.8***	-70.1***	-72.2***
	(-4.96)	(-4.32)	(-5.66)	(-4.60)
Number of observations	217	156	217	156
R^2	0.291	0.322	0.120	0.121
C. Average, all industries	$/Employee		log($/Employee)*100	
	Weighted (9)	Unweighted (10)	Weighted (11)	Unweighted (12)
Critical Industries	9896.39***	10468.28***	916.29***	922.35***
	(19.20)	(32.11)	(149.01)	(271.56)
Non-Critical Industries	9547.23***	10406.72***	909.68***	921.24***
	(13.59)	(48.00)	(108.62)	(401.51)
Diff: Non-Critical-Critical	-349.16	-61.56	-6.62	-1.11
	-0.40	-0.16	-0.64	-0.27
Number of observations	217	217	217	217

Panel A of table reports the coefficients estimates analogous to equation (4) in the document looking at the correlation between dollars of PPP funding per employee and Covid work exposure using March 2020 BLS employment-weighted and unweighted specifications (t-statistics in parantheses). Panel B reports the same specification except that the dependent variable is the log of $PPP per employee. Odd-numbered columns repeat the analysis for the subsample of non-critical industries. The dependent variable is expressed in percentage points and constructed using private sector employment data from the BLS' April 2020 employment report at the 4-digit NAICS level. Standard errors are robust to heteroskedasticity (White, 1980). The list of critical industries at the 4-digit NAICS level is in Appendix Table A.1. Panel C reports the average of the dependent variable for critical and non-critical industries, respectively, as well as the difference between the two averages. The cross-sectional standard deviation across BLS industries of the COVID factor exposure is 13.86%. Given that BLS only reports data for a single 4 digit agricultural industry (logging), we exclude agriculture from this analysis, though the results are not sensitive to this choice.

Appendix Tables and Figures

Table A.1: List of Critical Industries

NAICS Code	Industry Name
1111	Oilseed and Grain Farming
1112	Vegetable and Melon Farming
1113	Fruit and Tree Nut Farming
1119	Other Crop Farming
1121	Cattle Ranching and Farming
1122	Hog and Pig Farming
1123	Poultry and Egg Production
1124	Sheep and Goat Farming
1129	Other Animal Production
1141	Fishing
1142	Hunting and Trapping
1151	Support Activities for Crop Production
1152	Support Activities for Animal Production
2121	Coal Mining
2122	Metal Ore Mining
2123	Nonmetallic Mineral Mining and Quarrying
2131	Support Activities for Mining
2211	Electric Power Generation, Transmission and Distribution
2212	Natural Gas Distribution
2213	Water, Sewage and Other Systems
2373	Highway, Street, and Bridge Construction
3111	Animal Food Manufacturing
3112	Grain and Oilseed Milling
3113	Sugar and Confectionery Product Manufacturing
3114	Fruit and Vegetable Preserving and Specialty Food Manufacturing
3115	Dairy Product Manufacturing
3116	Animal Slaughtering and Processing
3117	Seafood Product Preparation and Packaging
3118	Bakeries and Tortilla Manufacturing
3119	Other Food Manufacturing
3121	Beverage Manufacturing
3254	Pharmaceutical and Medicine Manufacturing
3256	Soap, Cleaning Compound, and Toilet Preparation Manufacturing
3261	Plastics Product Manufacturing
3312	Steel Product Manufacturing from Purchased Steel
3313	Alumina and Aluminum Production and Processing
3331	Agriculture, Construction, and Mining Machinery Manufacturing
3391	Medical Equipment and Supplies Manufacturing
4242	Drugs and Druggists' Sundries Merchant Wholesalers
4245	Farm Product Raw Material Wholesalers
4413	Automotive Parts, Accessories, and Tire Stores

Table A.1: List of Critical Industries (cont)

NAICS Code	Industry Name
4441	Building Material and Supplies Dealers
4451	Grocery Stores
4452	Specialty Food Stores
4453	Beer, Wine, and Liquor Stores
4461	Health and Personal Care Stores
4471	Gasoline Stations
4523	General Merchandise Stores, including Warehouse Clubs and Supercenters
4539	Other Miscellaneous Store Retailers
4541	Electronic Shopping and Mail-Order Houses
4812	Nonscheduled Air Transportation
4841	General Freight Trucking
4842	Specialized Freight Trucking
4851	Urban Transit Systems
4852	Interurban and Rural Bus Transportation
4853	Taxi and Limousine Service
4859	Other Transit and Ground Passenger Transportation
4861	Pipeline Transportation of Crude Oil
4862	Pipeline Transportation of Natural Gas
4885	Freight Transportation Arrangement
4911	Postal Service
4921	Couriers and Express Delivery Services
4922	Local Messengers and Local Delivery
4931	Warehousing and Storage
5173	Telecommunications Resellers
5179	Other Telecommunications
5211	Monetary Authorities-Central Bank
5221	Depository Credit Intermediation
5222	Nondepository Credit Intermediation
5223	Activities Related to Credit Intermediation
5231	Securities and Commodity Contracts Intermediation and Brokerage
5232	Securities and Commodity Exchanges
5239	Other Financial Investment Activities
5241	Insurance Carriers
5242	Agencies, Brokerages, and Other Insurance Related Activities
5251	Insurance and Employee Benefit Funds
5259	Other Investment Pools and Funds
5411	Legal Services
5412	Accounting, Tax Preparation, Bookkeeping, and Payroll Services
5621	Waste Collection
5622	Waste Treatment and Disposal
5629	Remediation and Other Waste Management Services
6111	Elementary and Secondary Schools
6211	Offices of Physicians

Table A.1: List of Critical Industries (cont)

NAICS Code	Industry Name
6214	Outpatient Care Centers
6215	Medical and Diagnostic Laboratories
6216	Home Health Care Services
6219	Other Ambulatory Health Care Services
6221	General Medical and Surgical Hospitals
6223	Specialty (except Psychiatric and Substance Abuse) Hospitals
6231	Nursing Care Facilities (Skilled Nursing Facilities)
6233	Continuing Care Retirement Communities and Assisted Living Facilities for the Elderly
9211	Executive, Legislative, and Other General Government Support
9221	Justice, Public Order, and Safety Activities
9231	Administration of Human Resource Programs
9241	Administration of Environmental Quality Programs
9251	Administration of Housing Programs, Urban Planning, and Community Development
9261	Administration of Economic Programs
9271	Space Research and Technology
9281	National Security and International Affairs

Table A.2: Covid-19 Factor, portfolio weights (4-Digit NAICS)

Industry (NAICS)	Portfolio Weight (%)
4481: Clothing Stores	19.67
5613: Employment Services	15.95
7225: Restaurants and Other Eating Places	14.62
7211: Traveler Accommodation	11.23
4811: Scheduled Air Transportation	11.05
5151: Radio and Television Broadcasting	8.19
4522: Department Stores	6.12
7223: Special Food Services	5.99
3363: Motor Vehicle Parts Manufacturing	5.59
4831: Deep Sea, Coastal, and Great Lakes Water Transportation	5.57
3361: Motor Vehicle Manufacturing	5.51
3344: Semiconductor and Other Electronic Component Manufacturing	4.50
3329: Other Fabricated Metal Product Manufacturing	3.66
4411: Automobile Dealers	3.04
3339: Other General Purpose Machinery Manufacturing	2.76
7131: Amusement Parks and Arcades	2.75
3221: Pulp, Paper, and Paperboard Mills	2.66
5617: Services to Buildings and Dwellings	2.45
4244: Grocery and Related Product Merchant Wholesalers	2.28
5121: Motion Picture and Video Industries	2.10
3262: Rubber Product Manufacturing	2.02
3222: Converted Paper Product Manufacturing	1.96
4511: Sporting Goods, Hobby, and Musical Instrument Stores	1.90
3311: Iron and Steel Mills and Ferroalloy Manufacturing	1.88
2382: Building Equipment Contractors	1.63
2371: Utility System Construction	1.60
3252: Resin, Synthetic Rubber, and Artificial and Synthetic Fibers and Filaments Manufacturing	1.48
5616: Investigation and Security Services	1.44
3219: Other Wood Product Manufacturing	1.41
4431: Electronics and Appliance Stores	1.32
3353: Electrical Equipment Manufacturing	1.29
4482: Shoe Stores	1.29
4231: Motor Vehicle and Motor Vehicle Parts and Supplies Merchant Wholesalers	1.24
7132: Gambling Industries	1.19
7139: Other Amusement and Recreation Industries	1.14
3399: Other Miscellaneous Manufacturing	1.13
3141: Textile Furnishings Mills	1.12
2362: Nonresidential Building Construction	1.10
5152: Cable and Other Subscription Programming	1.09
8123: Drycleaning and Laundry Services	1.02
3152: Cut and Sew Apparel Manufacturing	1.02
3324: Boiler, Tank, and Shipping Container Manufacturing	1.01

Table A.2: Covid-19 Factor, portfolio weights (cont)

Industry (NAICS)	Portfolio Weight (%)
4236: Household Appliances and Electrical and Electronic Goods Merchant Wholesalers	1.00
2379: Other Heavy and Civil Engineering Construction	0.99
2361: Residential Building Construction	0.95
4532: Office Supplies, Stationery, and Gift Store	0.94
3359: Other Electrical Equipment and Component Manufacturing	0.90
3334: Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	0.90
3366: Ship and Boat Building	0.87
3323: Architectural and Structural Metals Manufacturing	0.77
3231: Printing and Related Support Activities	0.74
8121: Personal Care Services	0.74
6222: Psychiatric and Substance Abuse Hospitals	0.71
4422: Home Furnishings Stores	0.70
3322: Cutlery and Handtool Manufacturing	0.69
5611: Office Administrative Services	0.69
3352: Household Appliance Manufacturing	0.66
3272: Glass and Glass Product Manufacturing	0.66
3362: Motor Vehicle Body and Trailer Manufacturing	0.66
5615: Travel Arrangement and Reservation Services	0.61
7113: Promoters of Performing Arts, Sports, and Similar Events	0.61
6244: Child Day Care Services	0.61
3332: Industrial Machinery Manufacturing	0.61
3251: Basic Chemical Manufacturing	0.55
3279: Other Nonmetallic Mineral Product Manufacturing	0.53
3371: Household and Institutional Furniture and Kitchen Cabinet Manufacturing	0.51
3169: Other Leather and Allied Product Manufacturing	0.47
3369: Other Transportation Equipment Manufacturing	0.45
5614: Business Support Services	0.43
3325: Hardware Manufacturing	0.41
3372: Office Furniture (including Fixtures) Manufacturing	0.35
4483: Jewelry, Luggage, and Leather Goods Stores	0.33
3379: Other Furniture Related Product Manufacturing	0.33
2383: Building Finishing Contractors	0.33
4237: Hardware, and Plumbing and Heating Equipment and Supplies Merchant Wholesalers	0.32
7111: Performing Arts Companies	0.31
3351: Electric Lighting Equipment Manufacturing	0.28
8129: Other Personal Services	0.25
5619: Other Support Services	0.23
3212: Veneer, Plywood, and Engineered Wood Product Manufacturing	0.22
4238: Machinery, Equipment, and Supplies Merchant Wholesalers	0.19
3321: Forging and Stamping	0.18
3273: Cement and Concrete Product Manufacturing	0.18

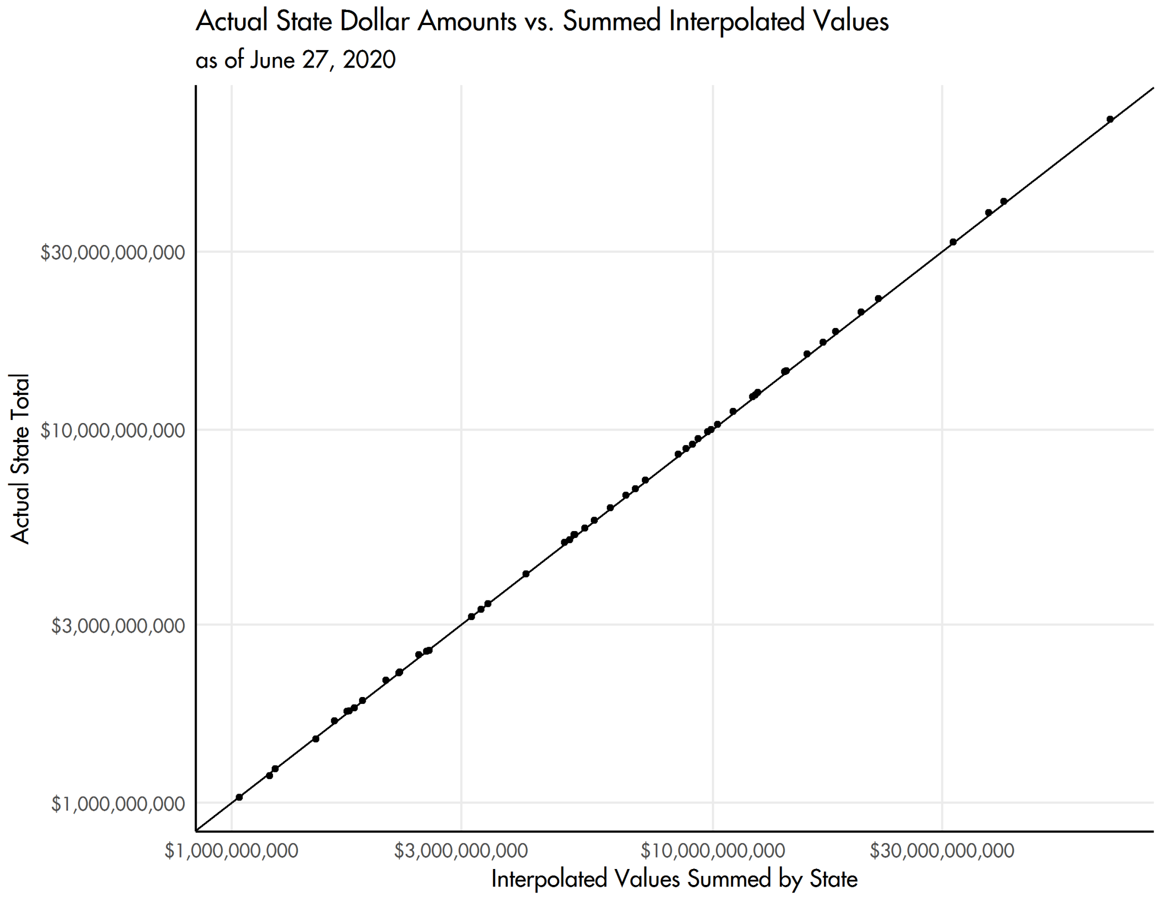
Table A.2: Covid-19 Factor, portfolio weights (cont)

Industry (NAICS)	Portfolio Weight (%)
6116: Other Schools and Instruction	0.15
3326: Spring and Wire Product Manufacturing	0.15
3132: Fabric Mills	0.15
4412: Other Motor Vehicle Dealers	0.14
4512: Book Stores and News Dealers	0.14
4832: Inland Water Transportation	0.13
3259: Other Chemical Product and Preparation Manufacturing	0.09
4883: Support Activities for Water Transportation	0.09
4421: Furniture Stores	0.08
5612: Facilities Support Services	0.08
3274: Lime and Gypsum Product Manufacturing	0.07
4881: Support Activities for Air Transportation	0.06
7224: Drinking Places (Alcoholic Beverages)	0.05
4869: Other Pipeline Transportation	0.04
4543: Direct Selling Establishment	0.04
2372: Land Subdivision	0.03
3211: Sawmills and Wood Preservation	0.03
6213: Offices of Other Health Practitioners	0.03
3335: Metalworking Machinery Manufacturing	0.02
4247: Petroleum and Petroleum Products Merchant Wholesalers	0.01
4889: Other Support Activities for Transportation	0.01
4243: Apparel, Piece Goods, and Notions Merchant Wholesalers	0.01
3327: Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	0.00
4442: Lawn and Garden Equipment and Supplies Stores	0.00
7114: Agents and Managers for Artists, Athletes, Entertainers, and Other Public Figures	0.00
8111: Automotive Repair and Maintenance	0.00
7112: Spectator Sports	0.00
4239: Miscellaneous Durable Goods Merchant Wholesalers	-0.01
5174: Satellite Telecommunications	-0.05
8122: Death Care Services	-0.09
4251: Wholesale Electronic Markets and Agents and Brokers	-0.09
4241: Paper and Paper Product Merchant Wholesalers	-0.09
5414: Specialized Design Services	-0.10
2111: Oil and Gas Extraction	-0.15
4246: Chemical and Allied Products Merchant Wholesalers	-0.24
3343: Audio and Video Equipment Manufacturing	-0.29
4233: Lumber and Other Construction Materials Merchant Wholesalers	-0.40
5419: Other Professional, Scientific, and Technical Services	-0.50
3333: Commercial and Service Industry Machinery Manufacturing	-0.52
4249: Miscellaneous Nondurable Goods Merchant Wholesalers	-0.57
5111: Newspaper, Periodical, Book, and Directory Publishers	-0.60
5418: Advertising, Public Relations, and Related Services	-1.05

Table A.2: Covid-19 Factor, portfolio weights (cont)

Industry (NAICS)	Portfolio Weight (%)
3241: Petroleum and Coal Products Manufacturing	-1.08
3336: Engine, Turbine, and Power Transmission Equipment Manufacturing	-1.32
5413: Architectural, Engineering, and Related Services	-1.93
5416: Management, Scientific, and Technical Consulting Services	-2.33
3255: Paint, Coating, and Adhesive Manufacturing	-2.70
5417: Scientific Research and Development Services	-2.91
4234: Professional and Commercial Equipment and Supplies Merchant Wholesalers	-3.14
3365: Railroad Rolling Stock Manufacturing	-3.47
3341: Computer and Peripheral Equipment Manufacturing	-5.69
3342: Communications Equipment Manufacturing	-10.47
3345: Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	-10.51
3364: Aerospace Product and Parts Manufacturing	-14.72
5112: Software Publishers	-16.97
5415: Computer Systems Design and Related Services	-31.57
5182: Data Processing, Hosting, and Related Services	-35.46
5191: Other Information Services	-41.46

Figure A.1: Accuracy of PPP interpolation method: Interpolated vs. Actual State Totals



This figure compares the aggregated loan dollar amounts constructed by the model's interpolation vs. the totals reported by the Small Business Administration as of Jun 27th, 2020. Because data are partially observed, the "Interpolated Values Summed by State" are taking the midpoint of each loan size bin and multiplying by a constant to adjust for a small multiplicative bias. All loans reported before Jun 27th, 2020 are summed by state and compared to reported values. This plot shows the debiased loan totals per employee, summed at the state level vs. the reported loan totals.